Tilburg University

Essays on the impact of different forms of collaborative R&D on innovation and technological change

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DOI:
10.26116/center-lis-2010

Publication date:
2020

Document Version
Publisher's PDF, also known as Version of record

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Nasiri, M. (2020). *Essays on the impact of different forms of collaborative R&D on innovation and technological change*. [Doctoral Thesis, Tilburg University]. CentER, Center for Economic Research. https://doi.org/10.26116/center-lis-2010

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R&D alliance is a multifaceted phenomenon, in which various socio-technological mechanisms operate in the interaction of partner firms. This dissertation is composed of three studies to shed light on different dimensions of firms' resources and performance in different forms of R&D collaborations. These studies consider (1) how the partner firms differences with respect to different dimensions of their knowledge bases influence inter-firm learning in dyadic R&D alliances, (2) how the partner firm differences in their resources across locales influence the multi-partner alliance performances at both alliance and firm levels, and (3) how firms leverage R&D collaboration to navigate the dynamics of technology selection during technology change. The findings of these studies tie together to the extent that they clarify the complex dynamics that exist between individual firms and their alliance partners in order to realize individual and joint value. In general, this dissertation contributes to the strategy and technology management literature by elucidating the less-explored dimensions of the firm's resources and performance in R&D collaborations.

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ISBN: 978 90 5668 629 1
DOI: 10.26116/center-lis-2010

NR. 628

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MOHAMMAD NASIR NASIRI

TILBURG SCHOOL OF ECONOMICS AND MANAGEMENT

CentER Dissertation Series

Tilburg University

ESSAYS ON THE IMPACT OF DIFFERENT FORMS OF COLLABORATIVE R&D ON INNOVATION AND TECHNOLOGICAL CHANGE

Mohammad Nasir Nasiri

10 June 2020

ESSAYS ON THE IMPACT OF DIFFERENT FORMS OF COLLABORATIVE R&D ON INNOVATION AND TECHNOLOGICAL CHANGE

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University,

op gezag van de rector magnificus, Prof. dr. K. Sijtsma, in het openbaar te

verdedigen ten overstaan van een door het college voor promoties aangewezen

commissie in de Aula van Tilburg University

op donderdag 27 augustus 2020 om 13.30 uur

door

Mohammad Nasir Nasiri,

geboren te Aligodarz, Iran

promotores:	Prof. dr. G.M. Duijsters Prof. dr. N.G. Noorderhaven
copromotor:	Dr. Z. He
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Acknowledgements

My longstanding dream to work in academia comes true with the completion of this dissertation. It has been a quite long and challenging way since I decided to leave my job in the industry to pursue my passion. However, I never felt alone in this way to the extent that I could not easily find my own footprint when I look back. I am so blessed to have so many supportive people who have always trusted my way, encouraged me to fulfill my dream, and helped me to develop my academic skills.

Geert Duysters, you were the one who helped me to make it happen. You always believed in me, let me freely make my own mistakes, and encouraged me to find my own way. You were always available for me, and your vision played a key role in enabling me to focus my thinking and realize what I can or cannot accomplish. Moreover, your special attention to both my academic and family life helps me to practice a balance in my life style. Your supervision went beyond your academic duty. Thank you.

Zilin He, I cannot appreciate enough your selfless dedication and commitment to advance my academic career. I am grateful for the incredible time that you spend to teach me how to write coherently and to take a rigorous approach in empirical research. You were very responsive and helpful in your detailed comments and general advice. You showed me the path, though I am still at its beginning.

Niels Noorderhaven, I was fortunate to have your great support. You opened a new way to my research. Without the ASML project, I would feel that my engineering background and work experience is useless in academia. I also learnt a lot from your professional academic character and integrity. Thank you.

I would like also to sincerely thank the members of my doctoral committee: Professors Dries Faems, Myriam Cloodt, Roger Leenders, Shivaram Devarakonda, and Victor Gilsing.

The depth and variety of your constructive comments taught me how to develop my research skills further and helped me to push the quality of the dissertation forward. I am grateful to all of you.

I would like to gratefully thank our respondents in ASML, who generously shared their invaluable information with us. Particularly, the ASML research project would not have been possible without the great support of Richard George and Jos Benschop. Thank you!

Shivaram Devarakonda, you left undeniable footprints in my path. You helped me to develop my ideas at the early stages of my Ph.D. and generously shared your remarkable skills in empirical research. Even though you were not my supervisor, you were always available for me whenever I had a question, and what a pleasure to have you as a member of my committee on completion of my Ph.D..

Tal Simons, you were the first who believed in me and let me into the CentER Graduate School when I was looking for my own way to fulfill my dreams. I was fortunate to have your excellent support as my educational coordinator when you were at Tilburg University. Your strong character always inspired me, and I always enjoyed our brief but fruitful conversations.

Aswin van Oijen, you trusted me and let me teach in the excellent program of Strategic Management. You gave me the chance to engage in the development of our department contact with industry. All lets me enjoy my work experience in the academic world. Thank you!

I would like to thank Martin Goossen for being such a great colleague and supporter in the course of Strategy Analytics. I learnt a lot from your exceptional dedication to academic duties and your excellent teaching skills. You were also so kind to help me during my job market season. I would like to thank also Jean-Malik Dumas who generously shared his valuable experience in the course of Strategy Implementation, and Lien Denoo and Anindya

Ghosh for helping me to have a successful experience in the course of Corporate Entrepreneurship.

During my PhD, I was also fortunate enough to have fantastic cohorts and office mates who become my lifelong friends. Joshua, I am impressed with your unique personality and being such a great friend. Vilma, my good friend and new colleague, I am happy that we can keep working at UvA. Stephanie, you were the first one who shared your reading hours when I arrived in Tilburg. The squad of P1.137, Jacob, Tom, Roland, and Feng, how amazing room we had together, I always remember our great time there. Joris, you were a great and considerate office mate in the last few months of my stay at Tilburg University. You all have always been ready to help out, to chat, and to share a few laughs, even when I was not ready! Joyce, Vincent, Yasir, Joeri, and Peter, we shared a great time inside and outside of volleyball pitch, I already miss it. Miranda, I was apparently not good enough to learn board games, but I am happy that we could keep our friendship without playing any games. Joobin, I think that we can finally watch a movie together. I am honored to have such friends like you all.

And Susanne, such a great journey we have started together on the ASML project, and I am happy that there is still a long path in front of us to go together. I am grateful to you for being such a great research partner and friend.

I would like also to thank other members of our great department for their collegiality and help along the way, including Henk Akkermans, Nufer Ates, Evita Bartels, Yang Ding, Renate van Dommelen, Mehmet Donmez, Marjan Groen, Elena Golovko, Ank Habraken, Amin Khodabandeh, Cindy Kuijpers, Jeoren Kuilman, Xavier Martin, Louis Mulotte, Vesna Nedimovic, and Carol Ou.

And my life was going on outside academia, if there is any in the Ph.D.! My dear friends, Amin, Hoda, Somayyeh, and Vahid, how I was lucky to find you in the Netherlands, I

cannot imagine how my family life was going on in your absence. Back home, Alireza, Fakhra, Ghahhar, Golnaz, Mohammad Reza, Nima, Reza, Shahram, Shahrooz, and Pooyan, I can write a full dissertation about your influence in my life. Thanks for your great friendship.

Finally, I am indebted to my family. My mom, your excellence in teaching inspired me to be a teacher, and your resilience in your challenging life taught me to never give up. I am here in a position to write these lines because of you. My lovely sister, how I miss your kind eyes and your charming children in every single day that I was away to follow my dreams. Your unconditional love keeps my heart warm.

And I am most grateful to my love, Bahar. You have made many sacrifices and supported me in difficult times. I started my long journey just a few months after we got married, and since then you have mostly seen my back and reflection of my face on the computer screen. You believed in me and offered me your full support even though I never available to reciprocate. I am unlikely to fulfill all my promises to you, but I would like to dedicate this dissertation to you. And to my lovely daughter, Aida, who can say that her daddy is a teacher now.

Before inviting you to read further, I would like to close this acknowledgement with a passage from Will Durant. The way that he explained what makes our life meaningful and beautiful always inspires me: “Three thousand years ago a man thought that man might fly; and so he built himself wings, and Icarus his son, trusting them and trying to fly, fell into the sea. Undaunted, life carried on the dream. Thirty generations passed, and Leonardo da Vinci, spirit made flesh, scratched across his [outstanding] drawings, plans and calculations for a flying machine; and left in his notes a little phrase that, once heard, rings like a bell in the memory—"There shall be wings.” Leonardo failed and died; but life carried on the dream. Generations passed, and men said man would never fly, for it was not the will of God. And

then man flew. Life is that which can hold a purpose for three thousand years and never yield. The individual fails, but life succeeds. The individual dies, but life, tireless and undiscourageable, goes on, wondering, longing, planning, trying, mounting, attaining, longing" (Durant, 1934; p. 621-622).

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CHAPTER 1

GENERAL INTRODUCTION

The "Information Age" has dramatically changed the competitive landscape. Technological knowledge has replaced capital goods as the main source of competitive advantage, and technological innovations have become the game changers that frequently punctuated the dominant practices of industries. Dealing with novel problems in this uncertain and fast changing environment has made firms more dependent to each other. Firms engage more frequently in different forms of interorganizational relationships (IOR) to share the cost and risk of their problem-solving activities. In particular, inter-firm R&D collaborations play an important role during technology change, when new technologies compete with each other as well as with the existing technology and the outcome of these technological battles is unknown ex ante.

Interorganizational research has investigated the attributes of the firms' resources as a crucial factor in the formation (Yayavaram et al., 2018), the choice of governance mode or organization (Oxley & Sampson, 2004), and the performance of different forms of R&D collaborations such as bilateral alliances (Nooteboom et al., 2007; Sampson, 2007) and multilateral alliances (Lavie, 2007; Olk & Young, 1997). It has underlined a fundamental contradiction between the diversity and utilizability of knowledge resources in R&D alliances: the difference between the firms' knowledge increases the value creation opportunities but reduces their capabilities to utilize these opportunities (Inkpen, 2005; Inkpen & Tsang, 2007). Alliance is a multifaceted phenomenon. Firms are engaged in alliances with different types of resources and for different purposes. However, while prior research has greatly contributed to our understanding of this contradiction, it has mainly taken knowledge resources in a generic form and overlooked the different dimensions or loci of knowledge. Therefore, our knowledge about firm's different knowledge resources in R&D alliances and their performance consequences has remained relatively limited. Furthermore, the current research has mainly focused on one dimension of R&D alliance performance, namely innovative performance, overlooking the other performance implications of R&D alliances especially in orchestrating industrial actors in the selection of new technology during technological change.

This dissertation attempts to improve the understanding of multidimensionality of firms' resources and performance in R&D collaboration. It aims to provide insight into *how the differences between partner firm's resources along different dimensions of partner firms' resources influence the inventive performance of R&D alliances, and how firms can leverage R&D alliances to influence the technology selection processes during the technology change*.

This dissertation providea theoretical explanation and empirical evidence to address these under-researched yet theoretically and managerially important aspects of R&D collaboration. Specifically, the three essays that constitute the main body of the dissertation consider respectively: (1) *How the partner firms differences with respect to different dimensions of their knowledge bases influence inter-firm learning in dyadic R&D alliances*, (2) *How the partner firm differences in their resources across locales influence the multi-partner alliance performances at both alliance and firm levels*, and (3) *How firms leverage R&D collaboration to navigate the dynamics of technology selection during technology change*.

Cognitive Distance and Inter-firm Learning in R&D Alliances

In the first essay (Chapter 2), I examine the performance consequence of difference between firms' knowledge bases in R&D alliances. Past research has found the fundamental contradiction between potential access to new knowledge and absorptive capacity alongside knowledge distance. While knowledge access increases with knowledge distance, firm's absorptive capacity decreases with knowledge distance; the interplay between these two contradictory mechanisms yields an inverted U-shape relation between knowledge distance and alliance performance hypothesized in this literature. However, prior research has only focused on one attribute of firm's knowledge base, that is, knowledge domain that addresses the different areas within which firms have accumulated knowledge over time. Another important attribute of firm's knowledge base has been overlooked, the between-domain knowledge or the knowledge that firms use to employ their knowledge domains together, namely knowledge architecture.

In this study, I revisit this approach. I employ the notion of cognitive distance to address the difference between firms' knowledge bases. Cognitive distance represents the difference between the firm's understanding of their environment as well as their problem solving approaches (Nooteboom, 2000). I argue that firm's cognition is a function of not only its knowledge in different domains, but also the way that it utilizes these knowledge domains together, so I extend the notion of cognitive distance based on two dimensions: knowledge domain and knowledge architecture. I examine the impact of cognitive distance alongside each of these dimensions on inter-firm learning as one of the main proxies of R&D alliance performance.

I concur with the prior literature findings that absorptive capacity decreases with knowledge domain distance, but I posit that knowledge access does not significantly changes with knowledge domain distance, as the R&D alliance does not provide enough space to access new knowledge domains. I argue that partner firms mainly learn from the distinct ways that they use their knowledge to understand and solve their common problem, rather than the difference of firms' knowledge domains. Therefore, I theorize that the potential access to new knowledge increases with knowledge architecture distance, interacting with decreasing firm's absorptive capacity, and hypothesize an inverted U-shape relation between knowledge architecture distance and inter-firm learning.

Moreover, I explicitly model firm-level absorptive capacity as relevant moderators, whereas the current approach in the literature lumps together absorptive capacity and knowledge accessibility into a function of distance between firms, leaving out the firm's in-house knowledge resources that form a very large part of its absorptive capacity. I examine how a firm's absorptive capacity alongside each knowledge dimension conditions the relation between cognitive distance and inter-firm learning. I hypothesize that the span of firm's knowledge domains, namely firm's knowledge breadth, alleviates the negative effect of knowledge domain distance on inter-firm learning. In addition, the malleability of firm's knowledge architecture, namely firm's knowledge decomposability, increases the firm's capacity to benefit from higher levels of knowledge architecture distance in R&D alliances.

Multi-Partner R&D Alliance Diversity and Performance

In the second essay (Chapter 3), I examine the performance consequences of different dimensions of multipartner alliance diversity. Most researchers have mainly examined the performance consequence of within-firm resources and fallen short to address the ex-boundaries resources that firms share in their alliances. However, MPAs as a multifaceted phenomenon cannot be simply explained only in this single dimension, as participating firms join MPAs with different attributes in terms of their internal resources and capabilities, their relational resources with their counterparts in MPA, and their status in the global alliance network. In addition, this stream of research has not distinguished and separately examined performance at the alliance level and the firm level, assuming that what is created at the alliance level can be proportionally appropriated at the firm level.

In this study, I reconceptualize multi-partner alliance (MPA) diversity based on the locus of the firm's resources and empirically examine their performance consequences at both alliance and firm levels. I dimensionalize the MPA diversity construct with respect to the resources that firms share in their alliance and that are located within the firms, between the firms, and across the global network of firms, respectively. I identify three dimensions of MPA diversity: 'partner variety' to address the diversity of within-firm resources, 'relational separation' to address the diversity of between-firm resources (i.e., prior tie strength), and 'status disparity' to address the diversity of network resources (i.e., status). I separately examine the performance consequence of each dimension at the alliance level as well as the firm level.

I indicate the fundamental contradiction between the diversity and utilizability of resources in each dimension and argue that diversity in each of these dimensions has an inverted U-shaped relation with MPA performance, but these relations at the firm level are not aligned with the MPA level. Partner variety provides the MPA with more opportunities and resources to achieve its intended goal, but as the MPA's diversity in this dimension exceeds a certain point, MPAs' ability to exploit these opportunities sharply decreases. However, partner firms with narrower knowledge breadth do not proportionally benefit from partner variety in either case as much as their counterparts with broader knowledge do. Likewise, moderate relational separation among partner firms benefit MPAs the most, as partner firms may learn from novel information and knowledge from their less familiar partners, but excessive relational separation leads to dividedness in the MPA and hurts the alliance performance. Nevertheless, partner firms with a brokerage role in divided partnerships can extract a higher share of created value at the cost of their partners. Finally, while status disparity may ease coordination via higher status firms to a certain level, the inequality across an MPA with high disparity can disturb the required transparent multilateral interaction for efficient collaboration among the alliance partners, exerting a negative effect on MPA performance. However, partner firms with a higher status in the global alliance network can extract a higher share of created value at the cost of their low-status partners.

Leveraging R&D Collaborations to Navigate Technology Change

In the third essay (Chapter 4), I take a qualitative approach to study the socio-technological performance of collaborative R&D activities over the course of technological change. Researchers have mainly showed interest in general antecedents and consequences of R&D alliances in their studies, so they mainly wash out the other influential factors existing in social and environmental contexts of alliances. As the result, we know less, for example, about how R&D collaborations assist firms to manage the course of technological change. We specifically know less about how firms may leverage from the underlying socio-technological mechanisms of their alliances to influence the socio-technological mechanisms that drive the technology selection procedures during technology change.

In this study, I take a real option theory perspective to investigate how successful firms take advantage of R&D collaborations to probe different technological options over the course of technological change. Moreover, how they timely make commitment to and abandon their technological options by the formation and termination of their R&D collaborations to attain enough legitimacy and endorsement to take the lead in the emerging technologies.

As a whole, the dissertation advances our understanding of various socio-technological mechanisms that operate in R&D collaborations and explain multiple aspects of this complex phenomenon. I also hope that this dissertation will inspire new research on the other performance implications of technological-based interorganizational relations, so we can better understand this part of our connected world.

CHAPTER 2

COGNITIVE DISTANCE DIMENSIONS AND INTER-FIRM LEARNING: KNOWLEDGE DOMAIN AND KNOWLEDGE ARCHITECTURE DISTANCE

ABSTRACT

Extant research has employed a rather narrow concept of cognitive distance in inter-firm learning as consisting of knowledge-domain distance only. We widen this approach by conceptualizing cognitive distance based on two dimensions: knowledge domain distance and knowledge architecture distance. We theorize how inter-firm learning in R&D alliances varies along each dimension of cognitive distance. We test our theory on a sample of 278 dyadic R&D alliances in the semiconductor industry, identifying the technological scope of each alliance through content analysis. Our findings contradict the stylized inverted U-shape association between knowledge domain distance and firm learning conjectured in the literature, and show a negative association which is, however, attenuated by firm's knowledge breadth. We also find that firm learning maximizes at an optimal level of knowledge architecture distance, and this optimal level is a function of firm's knowledge decomposability.

Keywords: *R&D alliances; inter-firm learning; knowledge domain distance; knowledge architecture distance*

INTRODUCTION

Facing novel problems in dynamic environments, firms may choose R&D alliance to improve the performance of their inventive search (Caner et al., 2017; Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001; Hagedoorn, 1993). In this joint effort, firms share and apply their distinct knowledge to execute their alliance tasks. That makes R&D alliances a platform on which firms can learn from each other, provided that they have the required absorptive capacity to recognize and assimilate new knowledge (Inkpen, 2005; Lane & Lubatkin, 1998; Cohen & Levinthal, 1990).

Learning research poses a contradiction between the antecedents of inter-firm learning in R&D alliances. On one hand, the firms' access to new knowledge is theoretically higher when their knowledge bases are more different. On the other hand, their absorptive capacity to make use of new knowledge is higher when their knowledge bases are more similar (Dyer & Singh, 1998; Lane & Lubatkin, 1998; Mowery et al., 1996; Inkpen, 2005; Grant & Baden-Fuller, 2004). Addressing this contradiction, researchers have employed the notion of cognitive distance to conceptualize and operationalize between-firm knowledge difference (Nooteboom et al., 2007; Gilsing et al., 2008). Cognitive distance between two firms represents the difference between their understandings of the environment and their approaches in their inventive search based on their distinct prior knowledge and experience (Nooteboom, 2000). Therefore, access to new knowledge in R&D alliances increases with cognitive distance between firms, but at the same time firm's absorptive capacity to acquire this knowledge decreases, suggesting the existence of an optimal level of between-firm cognitive difference.

However, this stream of research conceptualizes and operationalizes cognitive distance on one basis, knowledge domain distance. Knowledge domains represent one attribute of a firm's knowledge base: the categories of knowledge that a firm uses to comprehend its environment and solve its problems. Nevertheless, it does not demonstrate how a firm maps its observation into these categories or makes use of them to solve its problem. In other words, it does not address the inter-domain links that form the architecture of a firm's knowledge base (Yayavaram & Ahuja, 2008). Ironically, the organizational learning literature suggests that the firm's cognitive map that serves a firm to understand its environment and solve its problems is mainly a function of knowledge architecture or the way that knowledge domains are connected and combined, rather than knowledge domains per se (Nooteboom, 2000; Yayavaram & Ahuja, 2008; Fleming & Sorenson, 2001; Gavetti & Levinthal, 2000).

In this study, we take a closer look into inter-firm learning mechanisms in alliances by reconceptualizing cognitive distance based on two distinct dimensions, knowledge domain and knowledge architecture. We elaborate on the influence of each dimension into underlying mechanisms of inter-firm learning and examine whether both dimensions give rise to the stylized inverted-U shape hypothesized in the literature, or that they exert differential influences. With respect to the knowledge domain dimension, we argue that R&D alliance is not a proper platform for inter-firm learning in this dimension. On one hand, firms cannot acquire knowledge in domains that they do not have developed the required absorptive capacity. On the other hand, the adequate access and time for the required developments is generally beyond the scope and capacity of alliance agreements. Thus, we hypothesize that knowledge domain distance and inter-firm learning have a negative relation. With respect to the knowledge architecture dimension, we posit that R&D alliance is a proper platform in which firms can learn from the distinct ways that they apply their knowledge domains to execute alliance task. However, while access to new knowledge increases with knowledge architecture distance, absorptive capacity decreases at the same time, yielding an inverted U-shape relation between knowledge architecture distance and inter-firm learning. Thus, the hypothesized relation in the literature holds in this dimension.

Moreover, we submit that considering absorptive capacity as subsumed into cognitive distance at the alliance level neglects within-firm absorptive capacity. We look into within-firm absorptive capacity alongside each knowledge dimension to have a separate and deeper understanding of the absorptive capacity mechanisms and to examine empirically how it interacts with cognitive distance to influence inter-firm learning. We argue that the span of firm's knowledge domains, namely firm's knowledge breadth, and the malleability of firm's knowledge architecture, namely firm's knowledge decomposability, represents two distinct dimensions of firm's absorptive capacity. We hypothesize that firm's knowledge breadth provides more chance for the firm to make use of knowledge domain distance in R&D alliances and alleviates the negative effect of knowledge domain distance on inter-firm learning. In addition, firm's knowledge decomposability increases the firm's capacity to benefit from higher levels of knowledge architecture distance in R&D alliances.

We test our theory on a sample of 278 R&D alliances in the semiconductor industry from 1990 to 2002. We analyze the content of each alliance agreement to identify the technological scope of each alliance and map it onto relevant patent sub-classes. Prior research includes indiscriminately the whole knowledge bases of two firms when operationalizing cognitive distance in inter-firm learning. However, an R&D alliance is an agreement with limited technological scope within which firms share their knowledge (Inkpen & Tsang, 2007; Khanna, 1998; Khanna et al., 1998). For example, Hitachi, Ltd. and Texas Instruments (TI) Inc. formed an R&D alliance in 1991 to collaborate in the joint development of 256-megabit dynamic random-access memory (DRAM) chips. It is unlikely that these two large leading competitors share their knowledge and expertise in any domains except those relevant to the development and application of DRAM. Therefore, the real impact of the within-scope distance may be exaggerated, deflated, or otherwise distorted in the overall distance measure. We take technological scope of R&D alliances into account to avoid this issue and substantially reduce noise in our cognitive distance measures.

Our results show that knowledge domain distance between firms has a negative effect on firm learning, though firm's knowledge breadth alleviates this negative effect. In addition, our results show that an optimal level of knowledge architecture distance maximizes firm learning, and this optimal level is higher for firms with a more decomposable knowledge base (i.e., the optimal level increases and shifts to the right with knowledge decomposability).

Our study offers a fresh insight into the antecedents of firm learning in alliances and extend the prior findings. We extend and reconceptualize cognitive distance based on two dimensions: knowledge domain distance and knowledge architecture distance. This approach allows us to fully utilize this concept to examine the boundaries of inter-firm learning in R&D alliances. Our findings show that the two distinct dimensions of cognitive distance are not both associated with inter-firm learning in an inverted-U shape as suggested in the literature. In other words, our findings show that the stylized inverted-U shape hypothesized in literature is theoretically sound, but it holds on the other undertheorized dimension of cognitive distance, knowledge architecture distance, rather than knowledge domain distance. These findings suggest that firm learning maximizes in R&D alliances in which firms have an intermediate knowledge architecture distance and a small knowledge domain distance. Taken together, these findings redefine the boundaries of inter-firm learning in R&D alliances and suggest R&D alliances as a proper vehicle for renewing knowledge architecture rather than acquiring knowledge in less familiar domains. This study also offers a novel insight into the construct of absorptive capacity. We employ two dimensions of absorptive capacity alongside each dimension of cognitive distance. Knowledge breadth represents the breadth of a firm's knowledge base or knowledge domains with which a firm comprehends its environment and acquire relevant knowledge. Knowledge decomposability represents the capacity of a firm to change the architecture of its knowledge base by adding new links to or altering the existing ones between its knowledge domains. Finally, our approach in identifying the technological scope of an alliance agreement may encourage future research in alliances, M&A, and other forms of inter-firm relations to identify and consider the technological scope of such agreements.

BACKGROUND: INTER-FIRM LEARNING IN R&D ALLIANCES

Strategic management literature underscores R&D alliances as a generic external inventive search and knowledge sourcing strategy (Hagedoorn, 1993; Bierly & Chakrabarti, 1996; Hagedoorn & Duysters, 2002). Through their joint search process, firms share their distinct knowledge to execute alliance tasks within the scope of the agreement, so they get access to new knowledge that would be otherwise inaccessible (Doz & Hamel, 1998; Inkpen, 2000; Khanna et al., 1998; Kogut, 1988). Firms may use this opportunity to learn from their alliance partners not only to execute alliance tasks, but also to enhance their own knowledge to operate in areas unrelated to the alliance activities (Inkpen & Tsang, 2007; Sampson, 2007).

There is a paradox (Inkpen, 2005), however, in inter-firm learning. On one hand, significant knowledge distance between firms provides firms with access to new knowledge beyond the firm's knowledge boundaries (Rosenkopf & Nerkar, 2001), implying that the greater the differences between firms, the greater the chance of learning. On the other hand, unrelated knowledge may have limited value, as the recipient firm cannot efficiently acquire and recombine new knowledge with existing one without the required absorptive capacity (Cohen & Levinthal, 1990; Grant & Baden-Fuller, 2004; Inkpen, 2000; Mowery et al., 1996).

Dealing with this paradox, extant research considers competing arguments for the advantages and disadvantages of knowledge distance between firms. Accordingly, as cognitive distance between firms in R&D alliances increases, partner firms’ access to new knowledge as an advantage for inventive search and inter-firm learning increases, but at the same time, mutual understanding and common knowledge background required to make use of it decrease. As a function of these two interacting latent linear mechanisms, an inverted U-shape relation between cognitive distance and firm learning is proposed. Advantages dominate disadvantages up to a certain level of cognitive distance, such that cognitive distance is positively associated with firm learning in alliance and its inventive performance; beyond this level, however, disadvantages dominate advantages, driving a negative relation between cognitive distance and firm learning. These studies conceptualize and operationalize cognitive distance as technological diversity (Sampson, 2007), technological distance (Gilsing et al., 2008), and cognitive distance per se (Nooteboom et al., 2007), and provide evidence of an optimal level of cognitive distance between firms. For example, Nooteboom et al. (2007) delineates that novelty value and absorptive capacity are two contradictory factors that determine the influence of cognitive distance. Their findings show that cognitive distance between firms has an inverted U-shape relation to firm inventive performance in alliances, as an indicator of firm learning.

This stream of research contributes greatly to our understanding of inter-firm learning, but not without limitations. It conceptualizes cognitive distance by a single variable of knowledge domain distance, leaving out the important dimension of knowledge architecture distance. In addition, it uses absorptive capacity only as a dyadic level mechanism and a function of cognitive distance between two firms, so it does not fully address the absorptive capacity of firms that influences their learnings. Finally, it overlooks the alliance scope in the conceptualization and operationalization of cognitive distance and inter-firm learning in R&D alliances.

In this study, we expand this stream of literature. We reconceptualize cognitive distance at the alliance level based on two attributes of knowledge base, namely knowledge domain distance and knowledge architecture distance. We also identify two firm-level moderators, namely knowledge breadth and knowledge decomposability, that allow us to have a separate and potentially deeper peek into the absorptive capacity mechanism and to examine empirically how it interacts with cognitive distance to influence inter-firm learning. Finally, we take the scope of alliance into account in both of our theoretical and empirical analyses, which has been overlooked so far.

COGNITIVE DISTANCE AND INTER-FIRM LEARNING IN ALLIANCES

In a continuous learning loop, firms use their cognition, based on their accumulated knowledge in their past experience, to drive their inventive search, which in turn adds a new experience to prior knowledge and adjusts the cognition (Gavetti and Levinthal, 2000). New experiences and the way that firms relate them to prior experiences reshape the firm's knowledge base. Therefore, two dimensions characterize the firm's knowledge base: the knowledge domains in which different content of a firm's knowledge can be categorized, and the links that connect these knowledge domains together.

In an R&D alliance, firms share their accumulated knowledge within the scope of the agreement to drive their joint inventive search; this collaboration also provides them with a unique learning opportunity (Doz & Hamel, 1998; Inkpen, 2000; Khanna et al., 1998; Kogut, 1988). For example, Hitachi, Ltd. and Texas Instruments (TI) Inc. formed an R&D alliance in 1992 to collaborate in the joint development of 256-megabit dynamic random-access memory (DRAM) chips. According to their alliance agreement, the participants planned to work together on all phases except actual production, which each was to undertake separately. First, we expect that these two large companies get involved in this alliance with knowledge and expertise relevant to the development and application of DRAM; it is indeed unlikely that Hitachi shares its knowledge in non-electric control systems or vehicle brake systems, or TI shares its expertise in producing chips for smart control of tire air pressure. Accordingly, our theoretical development and empirical analysis in this study will be focused on firms' technological knowledge that is relevant and applicable to the technological scope of alliances. It includes knowledge that directly addresses the technological scope of alliances, such as Hitachi and TI's knowledge in design and production of volatile memory (G11C[1]), and associated knowledge in closely connected areas, such as Hitachi's experience to apply its knowledge in memory in telecommunication systems (H04L), or TI's effort in utilizing magnetic measuring techniques in development of volatile memories (G01R). Once this scope is established, the relevant cognitive distance between firms can be defined over the knowledge that they share in alliances.

Looking at Hitachi and TI's knowledge domains in Fig.1, while Hitachi has used its knowledge of memory with knowledge in telecommunication systems (H04L) in specific cases, TI's knowledge profile does not show this record, and while TI uses its memory knowledge with magnetic measurement technology in some cases, this expertise is absent in Hitachi' profile. Considering the links that form their knowledge architecture, Hitachi and TI both naturally use their knowledge in volatile memory with strong links to CMOS technology (H01L), electric digital processing (G06F), and Pulse techniques (H03K). Nevertheless, the link between volatile memory knowledge and CMOS technology is stronger in TI, which implies TI has more experience in using CMOS technology in producing volatile memories like DRAM. On the other side, Hitachi's knowledge profile shows a stronger link between volatile memory and pulse techniques, which implies Hitachi has superior expertise in DRAM clock design.

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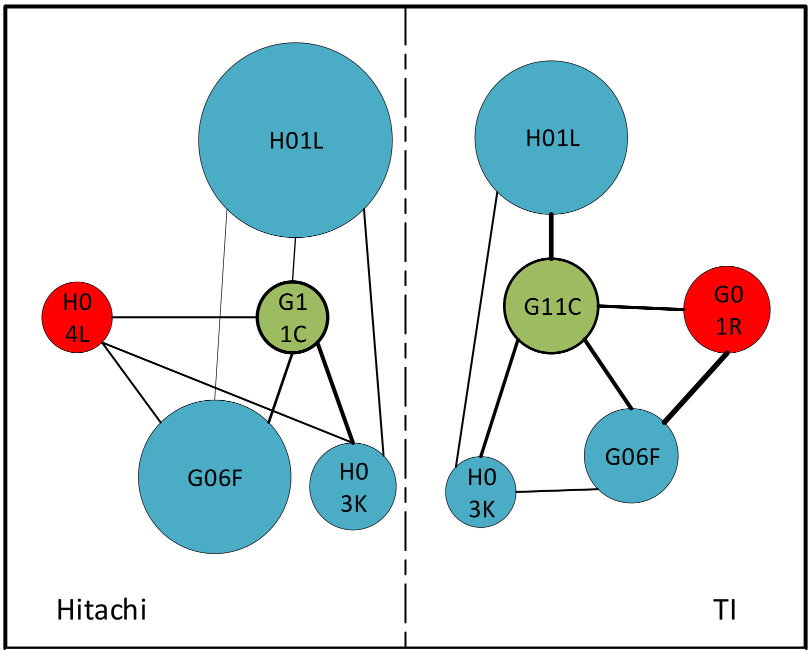
[1] CPC (Cooperative Patent Classification) is used to denote the technological knowledge domain of each company in this example and its corresponding figure. More explanation about this classification can be found in the Method section.

FIGURE 1: An excerpt of knowledge structure of Hitachi (left) and Texas Instrument (right) on 1991. The size of the node represents the level of knowledge that a firm possesses in the corresponding domains. The ties between the domains represents the inter-domain links. The thickness of the tie indicates the strength of links between the two domains. The size of the nodes and thickness of ties shown in the figure are for illustrative purposes. The figure just includes a selection of knowledge domains that are used in association with knowledge scope of alliance (G11C).



G01R: Magnetic measuring techniques
G06F: Electric digital processing
G11C: Design and production of volatile memory
H01L: CMOS technology
H03K: Pulse techniques
H04L: Telecommunication Systems

In the following, we examine the performance consequence of both dimensions of cognitive distance in R&D alliances, and in each dimension, we investigate the moderating effect of firm's absorptive capacity. For example, we examine TI's learning from Hitachi along their knowledge domain distance, such as the exposure to Hitachi's knowledge in telecommunication, new to TI, or to its profound knowledge in electric digital processing, less rich in TI. Then, we investigate how TI's knowledge breadth in the semiconductor industry conditions its learning from Hitachi. We also examine TI's learning from Hitachi along their knowledge architecture distance, such as Hitachi's higher expertise in using pulse techniques in volatile memory design. Then, we investigate how the TI' knowledge decomposability or its malleability in changing its knowledge architecture affects its benefit from this opportunity.

Knowledge Domain Distance

Extant research mainly uses knowledge domain distance to theorize and operationalize cognitive distance and predict an inverted-U shape relationship between it and firm learning in alliances. Accordingly, access to new knowledge domains increases with knowledge domain distance, but the required absorptive capacity to utilize this new knowledge decreases at the same time and outweighs its benefits after a certain point (Nooteboom et al., 2007; Sampson, 2007). In contrast, we argue that the acquisition of knowledge in less familiar or new domains is usually beyond the scope and capacity of R&D alliances, because the benefits of access to new knowledge domain are dampened by escalating recombination uncertainty, circumscribed by an alliance's limited scope and time, and discounted by alliance firms that need to specialize.

First, accessing knowledge in new domains may potentially provide the chance of adding novel combinations to a firm's knowledge (Kogut & Zander, 1992), but each new knowledge domain exponentially increases the number of possible combinations with multiple existing domains. Thus, the chance of finding a valuable combination actually decreases as recombination uncertainty increases (Fleming, 2001; Fleming & Sorenson, 2001). In addition, the chance of partner firms to pool their knowledge to share risk and enjoy economies of scale in their joint R&D efforts decreases when the knowledge distance increases (Yayavaram et al., 2018). Second, alliance agreements have limited scope and time, and firms deploy systematic safeguarding mechanisms to limit unintended knowledge transfer. Hence, R&D alliances do not usually provide enough space for the acquisition and combination of new knowledge domains (Grant & Baden-Fuller, 2004; Inkpen, 2000; Inkpen & Tsang, 2007). Finally, firms may still jointly use their complementary knowledge to address their common problem, without actually learning from each other, when their alliance tasks mainly involve pooled or sequential interdependence tasks, rather than reciprocal interdependence (Kavusan et al., 2016; Mowery et al., 1996; Gulati & Singh, 1998). In this case, firms focus their efforts to specialize in their own technological domains to develop complementary knowledge toward a joint outcome (Baldwin & Clark, 2000; Schilling, 2000), rather than learning from their counterpart's complementary knowledge.

With respect to firm's absorptive capacity, firms require prior knowledge and appropriate communication channels across knowledge domains to decompose, assimilate, and associate new knowledge with existing ones (Cohen & Levinthal, 1990; Kogut & Zander, 1992). A firm's knowledge is embedded in organizational elements such as its members, technological components, and tasks as well as the various subnetworks or communication channels formed by combining or crossing these elements (J. E. McGrath & Argote, 2001; Argote & Ingram, 2000, p. 153). Therefore, learning from new domains requires knowledge acquisition from all these elements and subnetworks, and combination of acquired knowledge with the existing embedded knowledge in the firm (Argote & Ingram, 2000). Generally, these developments take more time than limited duration of alliances. Thus, as the knowledge domain distance increases, the difficulty of acquisition and combination of knowledge in new domains exponentially increases; particularly, when firms aim to apply this new knowledge in a new context. In sum, as the knowledge domain distance between firms in R&D alliances increases, the firm's chance to develop the required in-house capabilities to absorb new knowledge significantly decreases.

Recalling the above-mentioned example, we expect that not only TI cannot acquire and utilize telecommunication technology from Hitachi in their alliances, but also having this new knowledge may impede TI’s learning from Hitachi’s expertise within the technological scope of the alliance, volatile memory.

Hypothesis 1: Knowledge domain distance in R&D alliances has a negative effect on firm learning in R&D alliances.

The Moderating Effect of Firm’s Knowledge Breadth

Although knowledge domain distance has a negative effect on firm learning, firms with a broader knowledge breadth may be less negatively influenced. Broad knowledge across different technological domains increases the chance of finding novel association and links between new and existing knowledge domains, so that recognition and assimilation of new knowledge will be easier (Cohen & Levinthal, 1990). In addition, experience of engaging in dispersed inventive searches and experiment with unknown combinations strengthen these firms’ capabilities to deal with recombination of new knowledge (Carnabuci & Operti, 2013; Gavetti & Levinthal, 2000).

Moreover, the practice of venturing with the creation and acquisition of new knowledge across different knowledge domains helps firms to develop inter-domain communication channels that facilitate the process of decomposition, transfer, and recombination of new knowledge (Caner et al., 2017; Zahra & George, 2002). This practice also strengthens the required organizational culture and structure to push firms beyond their knowledge boundaries (Argyres & Silverman, 2004; Carnabuci & Operti, 2013; Laursen & Salter, 2006).

All these factors ease the acquisition and integration of new knowledge, so as to reduce the negative effect of knowledge domain distance on firm learning in alliances.

Hypothesis 2: The negative effect of knowledge domain distance on firm learning in R&D alliances is weakened by firm's knowledge breadth.

Knowledge Architecture Distance

Knowledge architecture reveals how a firm makes use of its different knowledge domains together: which domains of knowledge are most likely to work well together and conversely, which ones are unrelated to each other and cannot be considered jointly (Yayavaram & Ahuja, 2008). In other words, knowledge architecture shapes the cognitive map, or the way that firms approach and formulate their problems and orient their inventive search (Gavetti & Levinthal, 2000; Levinthal, 1997; Simon, 1983). Given the idiosyncratic path of search processes and knowledge development in firms, each firm has a distinct knowledge architecture that can be the source of invention in an alliance.

Looking at the same problem from different perspectives in joint problem-solving activities allow firms to learn from the distinct patterns and new links with which they connect their knowledge domains and revisit their developed communication channels and filters within or across their organizational elements that form these patterns (Henderson & Clark, 1990; Kok et al., 2020). Learning from new patterns is not limited to knowing about the unexplored links between knowledge domains, but also entails awareness of the failed links that have been already tried in the development path of firms. Therefore, firms can use their distinct knowledge architecture to reduce iterations of trial and errors in their knowledge reconfigurations, and to adjust their cognitive maps in their inventive searches.

However, as architectural distance increases, the capability of firms to acquire and utilize this knowledge decreases. Significant difference in firms' cognitive maps harms the required mutual understanding to appreciate and combine different perspectives in collaborations (Nooteboom et al., 2007). Moreover, facing a disparate knowledge architecture with many new links may handicap firms in terms of recognizing and assimilating the new patterns that embedded in the subnetworks or communication channels across organizational elements (Henderson & Clark, 1990; Argote & Ingram, 2000).

Therefore, as knowledge architecture distance increases, the difficulty of its utilization increases in a way that after a certain point it outweighs its learning benefits.

Hypothesis 3: Knowledge architecture distance in R&D alliances has a curvilinear (inverted U-shape) effect on firm learning in alliances such that moderate distance yields maximum learning.

The Moderating Effect of Firm's Knowledge Decomposability

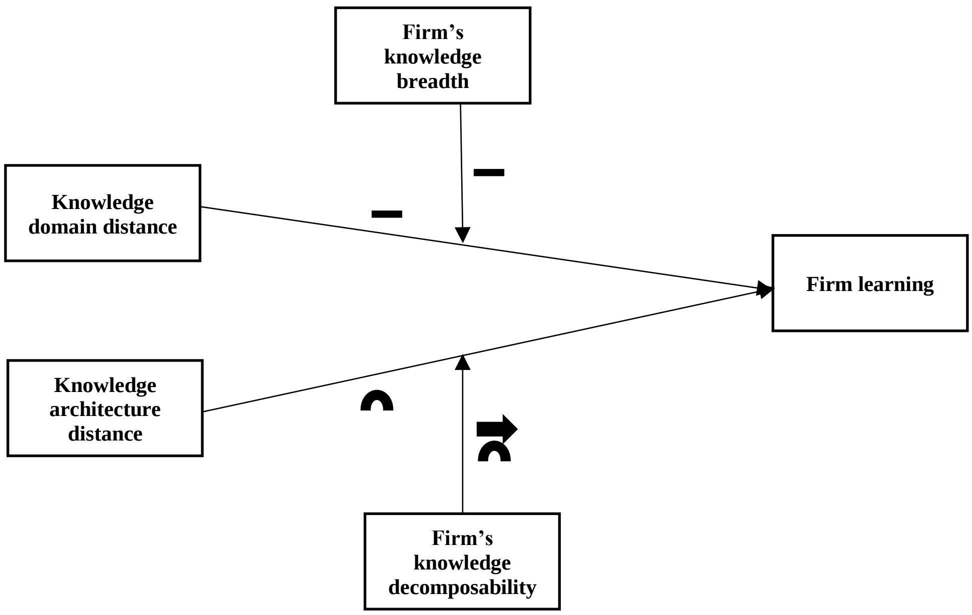
To benefit from knowledge architecture distance, firms should have the capability to make changes in their knowledge architectures. Extant research shows that the degree of decomposability of a firm's knowledge base, or knowledge decomposability in short, addresses its capacity for change or "malleability" in knowledge architecture (Yayavaram & Ahuja, 2008; Baldwin & Clark, 2000; Schilling, 2000; Simon, 1962). Knowledge decomposability indicates the extent to which knowledge architecture of a firm can be divided into clusters of domains. When links are distributed evenly across knowledge domains, identifying and decomposing clusters are difficult. However, when the distribution varies, clusters of highly connected knowledge domains which are loosely connected with each other appear, making knowledge architecture decomposable (Yayavaram & Ahuja, 2008; Nickerson & Zenger, 2004; Simon, 1962).

Firm's knowledge decomposability conditions the limit to which firms can take advantage of accessible knowledge architecture in R&D alliances. Firms with low knowledge decomposability, or in other words highly integrated knowledge, have limited malleability (i.e., capacity for change). Even a minor change requires significant reshuffling across the whole knowledge structure, as it is densely interconnected (Yayavaram & Ahuja, 2008). Moreover, the repetitive application of the same pattern over time limits the capability of firms to think of new patterns (Henderson & Clark, 1990; Levinthal & March, 1993). However, as knowledge decomposability increases, the malleability increases. The loose connections between and tight connections within knowledge clusters give firms enough background to recognize and assimilate other unexplored links and distinct patterns, and at the same time they leave enough space in the knowledge architecture to receive new links or accept the changes.

Therefore, as knowledge decomposability increases, the firm's capability to absorb and benefit from greater knowledge architecture distance increases.

Hypothesis 4: As firm's knowledge decomposability increases, the turning point of the inverted-U shape relation between knowledge architecture distance and firm learning in R&D alliances shifts to the right; that is, firms with a higher knowledge decomposability can benefit from greater knowledge architecture distance in alliances.

FIGURE 2: The theoretical model



METHODS

Empirical Design and Data

Empirical Design. We tested our theory in the context of R&D alliances in the semiconductor industry. We selected the semiconductor industry (SIC: 3674) because firms in this industry are regularly involved in the practice of patenting innovations, and its heterogeneous population provides considerable variations to test the hypotheses (Stuart, 2000). Firms in this industry also actively engage in alliances to address their rapidly changing competitive environment (Hagedoorn, 2002; Schilling, 2015).

Data. We collected alliance data from the JV & Alliance section of the SDC Platinum database. We found 414 R&D dyadic alliances that formed between 1990 and 2002 in the semiconductor industry, considering the SIC-Primary (i.e., SICP) flag of alliances. We chose this period to develop a balanced sample of observations over a complete circle of the alliance trend in this industry. The semiconductor industry has observed a boom in the formation of R&D alliances in the first half of this period, as they faced significant technological shocks and technological transitions, but a significant decrease in the second half after the emergence of Dot-com bubble crisis (Brown & Linden, 2011; Hagedoorn, 2002; Schilling, 2015; Zirulia, 2009). We identified 346 dyadic R&D alliances after re-checking the alliance status (i.e., completion), and removing alliances with undisclosed partners. We also compared the SDC information with that in the FACTIVA dataset to check all information such as alliance announcement dates and enhance alliance descriptions. Finally, we tracked historical alliances (all types of alliances, including dyadic alliances) all the way back to the year 1985 in order to ensure sufficient coverage of active alliances for the required analysis in this study.

We extracted the patents from the EPO Worldwide Patent Statistical Database (PATSTAT[2]). PATSTAT covers all registered patents in more than 100 patent offices that allows us to aggregate the registered patent at patent family level (DOCDB patent family) to cover all the relevant registered patents in different patent offices without over counting those

[2] PATSTAT Edition: 2017 Autumn; Classification Version: 2013.

registered in multiple offices. This database, as the NBER and the USPTO patent database, contains patent number, assignee name, filing year, and grant year, but not the CUSIP numbers (key identifier used in Compustat & the SDC databases) of the assignee firms, so matching of patents with identified firms in our sample is not straightforward. In addition, we used alliance data, rather than public semiconductor firms, as the starting point of our data collection, and we kept non-public firms in our sample to cover more R&D alliances and to improve the generalizability of our theory, but non-public firms do not have CUSIP which makes the matching procedure even more complicated.

Therefore, we took significant care in matching our firm list and patent data. First, we used the company directory list, who-owns-whom information, in LexisNexis to identify all divisions, subsidiaries, and joint ventures of each firm at the level of parent firm in the sample. We then used different online sources to trace each firm's history to account for name changes, division names, divestments, acquisitions, and joint ventures; and to obtain precise information also on the timing of these events. This process yielded a master list of entities that we used to identify all patents belonging to sample firms during the period of study. To match the corresponding patents to each firm, we first used the name-matching bridge between the NBER/USPTO patents and Compustat firms provided by Hall and colleagues (Hall et al., 2001), in which patent assignee names are standardized and matched with firm names in Compustat. However, we could find patent information for only 226 partner firms out of 392 partner firms[3], and we could not determine whether the rest of the firms had no patents or had patents but did not appear in this database. In addition, our sample is not limited to the public firms, and includes 133 non-public firms which are not recorded in Compustat. Therefore, we

[3] These numbers are very close to what Srivastava & Gnyawali (2011) reported in their similar procedure.

wrote a name-matching program to get additional patents for both public and non-public firms in our database. The resulting collected patents were granted between 1987 and 2005 to our sample firms. Finally, we dropped 68 alliances of non-patenting firms, as it was not possible to develop both independent and dependent variable measures, so the final sample of our study consists of 278 R&D alliances.

As large firms may diversify in different industries and technologies, relying on all their patent data might be misleading in our analysis (Sampson, 2007). To this end, we did a content analysis of the technological description of each alliance agreement to determine its technological scope. We obtained the technological descriptions from the SDC and FACTIVA. Then, we followed the patent office procedure for examiners to match these descriptions to specific technology sub-classes under the Cooperative Patent Classification (CPC) scheme (*Espacenet - Classification Search*, 2019; Hunt et al., 2012; White, 2010; Devarakonda & Reuer, 2018)[4]. The CPC is a common classification system for patent documentation that integrates the USPTO (American system) and the EPO (European System) and classifies technologies in hierarchical nested levels, such as section, class, subclass, and so on (*CPC*, 2019). In short, we made a brief, accurate summary of the technological description of each alliance, noted the key technical words, and searched for the synonyms. Then, we used the advanced search form in the EPO search engine, and search keywords and synonyms in the Title and Abstract fields to retrieve a list of the corresponding sub-classes. Finally, we retrieved the corresponding patent to each sub-class and reviewing their abstracts and top claims to check the relevancy of the patents to the technological scope of alliances (this procedure is explained in more details with an example in appendix 1). We checked this procedure with a patent

[4] https://worldwide.espacenet.com/classification?locale=en_EP

examiner at the EPO office in The Hague in the Netherlands. Then we compared the results on a random sample of 50 alliances in our data with the same examiner as well as a commercial patent search engine[5]. The results were consistent in 45 alliances at the sub-class level and in all 50 alliances at the class-level.

Measures

We used patents to construct the firm's knowledge base, the basis for our key measures. We followed the following procedure to reduce the common noise of patents in this process. First, we considered a three-year window in our study. We included those patents that their applications are filed in three years after the alliance formation for the post-alliance variable, a conservative choice based on trade-offs between the required time for firm learning in an alliance and recording such learning in the citations of subsequent patent applications, and the high rate of internal technology development within the firm. To consider the fast-changing technological knowledge in this industry and also to keep the balance between pre and post alliance variables, the same restriction was considered for the pre-alliance variables. Moreover, as the main CPC sub-class of each patent has been often co-listed with other CPC sub-classes, we followed Fleming and Sorenson (2001) and used this information to construct the firm's knowledge base.

We used the firm's knowledge base to develop our measures at two levels: alliance level independent variables that address the distance of firms in alliances as well as firm learning from its partner, and firm-level moderators and control variables. For the sake of accuracy, we took different approaches at each level. For alliance-level independent variables, we took the technological scope of alliances into account. We selected all the patents that at

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[5] Octamine patent search: *https://app.octimine.com/*

least one of their assigned technology sub-classes (i.e., CPC sub-classes) matched to the identified scope of alliances. In this way, we take into account the firms' knowledge that either directly addresses the technological scope of alliances, or closely associated with it. For the other firm-level variables, we followed Yayavaram and Ahuja (2008, p. 347) and Carnabucci and Operti (2013) by including all 56 sub-classes that are related to the semiconductor industry.

Dependent Variable at the firm level. Firm learning was measured as the number of total citations that a firm made to its counterpart's patents within the technological scope of the alliance within three years after the alliance formation, namely "firm's post alliance cross-citation". This measure is extensively used to measure knowledge diffusion and learning (Jaffe et al., 1993; Mowery et al., 1996a; Roach & Cohen, 2013). The alliance agreement has limited scope, so attributing all cross-cited patents between firms to a single alliance is not representative, so we reduced the noise by counting those patents that cite the counterpart's patents within the scope of the alliance.

Independent Variables at the alliance level. We used PATSTAT technology class data to identify the technological scope of each alliance and build our measures. Following Fleming (2001) and Fleming and Sorenson (2001), we considered the technology sub-classes assigned to patents as proxies for knowledge domains, and the co-listing of sub-classes as indicative of inter-domain links.

For knowledge domain distance, we measured the angular distance between firms' prior-alliance patents within the technological scope of alliances with respect to their technology sub-classes. The angular distance addresses the difference between the orientations of developed knowledge in different knowledge categories in firms. To this end, we first used Jaffe's angular proximity measure (Jaffe, 1986), and then calculate the distance measure. We indicated the technical position of a firm a in knowledge space as a vector of a firm's knowledge in distinct knowledge categories:

$$f_a = (f_{a1}, \dots, f_{ak}, \dots, f_{aK}) \qquad (1)$$

where f_{ak} is the fraction of firm *a*'s patent that are in patent sub-class k during the years *t-3* to *t-1*. Angular proximity between two firms *a* and *b*, then, is the cosine of the angle between their technological position as follows:

$$S_{ab} = \frac{\sum f_{ak} f_{bk}}{\sqrt{\sum f_{ak}^2 f_{bk}^2}} \qquad (2)$$

and the angular distance is $D_{ab} = 1 - S_{ab}$.

To operationalize knowledge architecture distance, we followed Yayavaram et al. (2018). We first developed a link matrix that represents the inter-domain knowledge links that form the architecture of knowledge that each firm shares in accordance with the alliance scope. Second, we compared these link matrices. We use an example to illustrate this procedure. To calculate the knowledge architecture distance between Hitachi and TI in their R&D alliance to develop volatile memories, we first calculated the strength of the links between all the patent subclasses in Hitachi that are either in the scope of its alliance with the TI (i.e. G11C) or connected to G11C (i.e. G06F, H03K, H01L, H04L) (Fig.1). For example, we calculate the likelihood of having two patent subclasses like G11C and G06F co-listed in the Hitachi's patents that indicates how much the corresponding knowledge to each of these sub-classes are used together compared to the other possible combinations. This yields a link matrix between all patent sub-classes, and represents the architecture of knowledge that Hitachi shares in its alliance with the TI. Thus, the strength of link between technology sub-classes *j* and *k* for the firm a, $L_{a,j-k}$, can be calculated as:

$$L_{a,j-k} = \frac{n_{jk}}{n_j + n_k + n_{jk}} \tag{3}$$

Where n_j is the number of firm a's patents that are assigned to sub-class j but not sub-class k, n_k is the number of patents that are assigned to sub-class k but not sub-class j, and n_{kj} is the number of patents that are assigned to both sub-classes. The link matrix L consisting of $L_{a,j-k}$ for all pairs of domains represents the structure of the firm's knowledge base (Yayavaram et al., 2018; Yayavaram & Ahuja, 2008).

Second, we compared the knowledge structure or link matrices of these firms to calculate their knowledge architecture distance. We measured knowledge architecture distance as the sum of the absolute difference between the corresponding links to all technology sub-class pairs that are common to both firms[6].

However, we calculated the strength of links between each patent sub-classes as the likelihood of having them co-listed in a patent, so the size and diversity of firm's knowledge base can influence this measure (Yayavaram & Ahuja, 2008). In other words, firms with larger and more diverse knowledge base have more possibility in recombination of its knowledge domains, so the likelihood of having two sub-classes co-listed in a patent is naturally lower than a firm with smaller and less diverse knowledge base. To remove the effect of size and diversity of firms' knowledge bases, we compare the percentile score of the strength of each link rather than their absolute value. To do so, we followed Yayavaram et al. (2018, p. 2288) and first use the number of patents (size) and the number of patent sub-classes to compute the

[6] In our data, we did not observe any R&D alliance in which firms did not have any patents in the scope of alliance.

percentile values of each link (i.e., 1st percentile, 2nd percentile, and so on, until 100th percentile) with the following power-law relationship:

Log (percentile value) = constant+α × log (size of the firm's knowledge base) + β × (the number of patent sub-classes) (4)

We then compare each firm's link strength with the predicted values. Based on these comparisons, we then computed the percentile score $p(L_{a,j-k})$ for each firm's links. We measured *Knowledge architecture distance* as the weighted sum of the absolute difference in percentile scores between the two firms for all technology sub-class pairs that are common to them.

$$\text{Knowledge Architecture Distance}_{a,b} =$$

$$\sum_{j,k} W_{a,b,j,k} \times |p(L_{a,j-k}) - p(L_{b,j-k})| \qquad (5)$$

The weight $W_{a,b,j,k}$ is equal to $(f_j^a + f_k^a)/2 + (f_j^b + f_k^b)$, where f_j^a(resp. f_k^a), *and* f_j^b(resp. f_k^b) represent the fraction of patents that belong to a technology sub-class j (resp. k) for firm *a* and firm *b*, respectively. We set the value of knowledge architecture distance to 0 when two firms had no common domain pairs and normalized its values to be more comprehensible and comparable to knowledge domain distance.

Moderator Variables at the firm level. To measure knowledge breadth, we focused on the distribution of patents across all semiconductor patent sub-classes (Carnabuci & Operti, 2013; Yayavaram & Ahuja, 2008), not just within the scope of alliances, and calculated the inverse of the nonbiased Herfindahl Index (HHI) proposed by Hall (2002, p. 3). This approach adjusts the bias caused by the size of the firm's patent portfolio (Hall, 2002). To this end, we calculated knowledge breadth as it follows:

$$\text{Knowledge breadth}_a = 1 - \left[\frac{N_a * HHI_a - 1}{N_a - 1}\right] \qquad (6)$$

Where $HHI_a = \sum_{k=1}^{K}\left[\frac{N_{ak}}{N_a}\right]^2$ where a= firm; k= patent sub-classes; N_{ak} = number of patents in sub-class k by the firm a; N_a= total number of patents in all sub-classes by the firm a. The index rises with the number of patent sub-classes a firm invents in and equality of its efforts across sub-classes, its value range from 0 to 1, with smaller value indicating that, adjusting for the size of the overall patent portfolio, a firm has narrower knowledge breadth.

To measure knowledge decomposability of the whole firm's knowledge base, we used the weighted clustering coefficient. The clustering coefficient addresses knowledge composability, as it measures the extent to which nodes in a network tend to cluster together. The non-weighted clustering coefficient for a patent sub-class with k_i links to other sub-classes (co-listed sub-classes) is defined as $CC_i = n_i/[k_i \times (k_i - 1)/2]$, where n_i is the number of links between the k_i neighbors (co-listed patents) of patent sub-class i. The denominator is the maximum number of links that are possible between k_i neighbors of patent-subclass i. Finally, the clustering coefficient for the whole knowledge base, *CC*, is CC_i averaged across all patent sub-classes (Yayavaram & Ahuja, 2008, pp. 350–351).

We followed the above procedure to measure knowledge decomposability, but we also considered the weight of links between patent sub-classes of firms in the semiconductor industry. We used the NW_WCC module of STATA to calculate the weighted clustering coefficient of all nodes in the above calculated link matrix (formula (3)) (Joyez, 2017; Saramäki et al., 2007)[7]. Then, we measured the degree of decomposability for the entire knowledge base

[7] Yayavaram and Ahuja (2008) built this measure by designing an elaborated procedure to distinguish strong and weak ties; however, we calculated the clustering coefficient of all ties and took all them into account.

as (1- knowledge composability). Thus, when nodes in the network have ties that are mostly within their clusters, the network has high decomposability and when the nodes in the network have ties that are mostly outside their clusters, the network has low decomposability.

Control Variables. We included several additional control variables to exclude alternative explanations. First, we included several firm-level controls. We controlled for the *Firm pre-alliance learning*, as the prior learning history between firms can ease their learning in alliances (Yang et al., 2015). We also controlled for *Firm's pre-alliance total in-scope patents*. This variable can help control for the firm's in-house R&D efforts within the alliance scope, as a more precise measure than the conventional aggregate R&D spending which entails all R&D activities of the firm (i.e., in- and ex-scopes) and is subject to accounting considerations (Sampson, 2007). Moreover, we control for *Firm's pre-alliance total patents*. This variable can also help control for firm (applicant) size, as it address the size of financial and non-financial resources that come with firm size (Sampson, 2007). We also control for *Firm's degree of centrality* to control for possible information channels that foster firm learning. We also used dummy variables to control for firms came from the semiconductor industry, *Firm's semiconductor industry dummy*, and the U.S., *US firm dummy*. Finally, we used a dummy variable to distinguish public firms from private firms, *Firm government-related dummy*.

Moreover, we control for all these variables for the partner firms, namely *Partner's pre-alliance total in-scope patents, Partner's pre-alliance total patents, Partner's degree of centrality, Partner's semiconductor industry dummy, US Partner dummy, Partner government-related dummy*. In addition, we controlled for *Partner's knowledge breadth*, and *Partner's knowledge decomposability*, as it can be argued that learning from firms with broader knowledge or more decomposable knowledge base might be easier.

At dyadic level, we controlled for *Number of prior alliances btw firms* in the semiconductor industry, excluding licensing agreements, to consider the possible effect of partner-specific experience in firm learning. We defined also dummy variables to control for Joint Ventures (*JV*), as well as *Cross border alliance dummy,* as prior suggested that JVs can provide a better platform for learning (Mowery et al, 1996), and international alliances demonstrate different attributes for firm learning in alliances (Lane, Salk, and Lyles, 2001).

Statistical Analysis

Since our dependent variable, the firm's post alliance cross-citation, is a count variable that has high variance relative to its mean, over-dispersed, we used negative binomial regression analysis. The likelihood-ratio (LR) test of dispersion parameter (i.e., α) shows α is significantly greater than zero in all our models, so confirming over dispersion in data and supporting our choice of negative binomial over poisson. Since we include both alliance partner firms in our analysis, a multi-level fixed effect model seems as the ideal choice, but the results of ANOVA test, as well as MLM itself, show that the higher-level variance at the alliance level is trivial (9.35 E-15), obviating the need to fit our data with multi-level models. Nevertheless, we report standard errors clustered at the alliance level, by using *vce (cluster alliance_id)* option in our estimation model in STATA, to relax the requirements that the observation must be independent.

RESULTS

Table 1 presents the descriptive statistics and correlations. The mean of *Firm's post alliance learning* (530) as well as *Firm's pre-alliance learning* (361) show that firms more intensively cite each other post-alliance than pre-alliance ($p<0.001$ in t-test). The mean of normalized *Knowledge architecture distance* is lower than *knowledge domain distance* as we used in-scope *knowledge that was common between firms to measure Knowledge architecture*

TABLE 1: Descriptive Statistics and Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	**Firm's post alliance learning**	1.00																						
2	**Knowledge domain distance**	-0.19	1.00																					
3	**Knowledge architecture distance**	0.44	-0.29	1.00																				
4	**Firm's knowledge breadth**	0.28	-0.38	0.23	1.00																			
5	**Firm's knowledge decomposability**	0.22	-0.39	0.19	0.82	1.00																		
6	**Firm's pre-alliance learning**	0.94	-0.19	0.45	0.28	0.21	1.00																	
7	**Firm's pre-alliance total in-scope patents**	0.74	-0.21	0.48	0.24	0.20	0.71	1.00																
8	**Firm's pre-alliance total patents**	0.72	-0.25	0.44	0.44	0.29	0.79	0.60	1.00															
9	**Firm's degree centrality**	0.52	-0.26	0.34	0.43	0.32	0.52	0.45	0.64	1.00														
10	**Firm's semiconductor industry dummy**	-0.13	0.03	-0.13	-0.14	-0.03	-0.16	-0.13	-0.27	-0.03	1.00													
11	**US Firm dummy**	0.00	0.15	-0.10	-0.13	-0.09	-0.04	0.03	-0.18	-0.07	0.08	1.00												
12	**Firm government-related dummy**	-0.07	0.00	0.04	-0.03	0.03	-0.07	-0.04	-0.08	-0.01	0.05	-0.13	1.00											
13	**Partner's pre-alliance in-scope patents**	0.04	-0.21	0.48	0.01	0.04	0.05	0.13	0.02	0.10	-0.01	0.00	0.09	1.00										
14	**Partner's pre-alliance total patents**	0.01	-0.25	0.44	0.05	0.07	0.00	0.02	0.00	0.05	0.04	-0.18	0.13	0.60	1.00									
15	**Partner's degree centrality**	0.05	-0.26	0.34	0.04	0.02	0.04	0.10	0.05	0.03	-0.04	-0.06	0.00	0.45	0.64	1.00								
16	**Partner's semiconductor industry dummy**	0.01	0.03	-0.13	-0.10	-0.06	0.04	-0.01	0.04	-0.04	0.00	0.06	-0.04	-0.13	-0.27	-0.03	1.00							
17	**US Partner dummy**	-0.04	0.15	-0.10	-0.12	-0.11	-0.07	0.00	-0.18	-0.06	0.06	0.45	-0.08	0.03	-0.18	-0.07	0.08	1.00						
18	**Partner government-related dummy**	0.11	0.00	0.04	0.03	-0.03	0.19	0.09	0.13	0.00	-0.04	-0.08	-0.02	-0.04	-0.08	-0.01	0.05	-0.13	1.00					
19	**Partner's knowledge breadth**	0.02	-0.38	0.23	0.13	0.10	0.00	0.01	0.05	0.04	-0.10	-0.12	0.03	0.24	0.44	0.43	-0.14	-0.13	-0.03	1.00				
20	**Partner's knowledge decomposability**	0.06	-0.39	0.19	0.10	0.09	0.06	0.04	0.07	0.02	-0.06	-0.11	-0.03	0.20	0.29	0.32	-0.03	-0.09	0.03	0.82	1.00			
21	**Number of prior alliances btw firms**	0.47	-0.27	0.48	0.28	0.23	0.45	0.38	0.48	0.56	-0.07	-0.07	-0.01	0.38	0.48	0.56	-0.07	-0.07	-0.01	0.28	0.23	1.00		
22	**Cross border alliance dummy**	-0.01	-0.05	0.01	0.04	0.03	-0.01	-0.01	0.06	0.06	0.09	-0.21	-0.01	-0.01	0.06	0.06	0.09	-0.21	-0.01	0.04	0.03	-0.01	1.00	
23	**JV dummy**	-0.01	-0.07	-0.02	0.09	0.07	-0.02	0.02	0.01	-0.05	-0.06	-0.08	-0.02	0.02	0.01	-0.05	-0.06	-0.08	-0.02	0.09	0.07	-0.06	-0.07	1.00
	Mean	530.13	0.40	0.19	0.74	0.86	361.09	119.11	1205.13	0.01	0.33	0.59	0.02	119.11	1205.13	0.01	0.33	0.59	0.02	0.74	0.86	24.64	0.32	0.15
	S.D.	1029.96	0.43	0.19	0.29	0.32	723.03	256.09	1734.87	0.01	0.47	0.49	0.13	256.09	1734.87	0.01	0.47	0.49	0.13	0.29	0.32	22.73	0.47	0.35
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	8476.00	1.00	1.00	0.98	1.00	8974.00	2471.00	13100.00	0.03	1.00	1.00	1.00	2471.00	13100.00	0.03	1.00	1.00	1.00	0.98	1.00	145.00	1.00	1.00

distance, rather than whole in-scope knowledge in *knowledge domain distance*. The relatively large mean of *Firm's knowledge breadth* and *Firm's knowledge decomposability* indicates that firms joined R&D alliances with relatively well-developed knowledge in the scope of alliances, so their knowledge is well recombined with other knowledge domains. The correlation among predictor variables are not critically high. We performed a diagnostic test using the "collin" procedure in Stata to check for multicollinearity issue. The test showed no VIF higher than 3 and the conditioning numbers of the models were all less 25, all less than the suggested threshold for VIF, 10, and conditioning number, 30 (Table 2) (Belsley & Kuh, 1993)[8].

Table 2 shows estimates of binomial regression models to test our hypotheses. Model 1 includes only the control variables. The interpretation on control variables can be subject to inaccuracy due to other possible explanations (Cinelli & Hazlett, 2018), so we just mention the most noticeable results with caution. The positive and significant coefficients of *Firm's pre-alliance total patents* and *Firm's semiconductor industry dummy* indicate the expectable higher absorptive capacity of large firms as well as semiconductor active firms. The positive and significant coefficient of *Firm's degree of centrality* confirms the role of network connections as a conduit that provides firms with complementary information to take advantage of their partners' knowledge.

In Model 2, the variable *Knowledge domain distance* is introduced to test H1. The results suggest a negative association between *Knowledge domain distance* and *Firm learning*. We followed Haans et al. (2016) and tested the *Knowledge domain distance squared* to rule out the possibility of a U-shape relation and providing support for the hypothesized linear

[8] We acknowledge that the collinearity test suits linear regression models, and although our test is common in extant research, the relevancy of the results should be consider with cautious. However, our robustness tests did not show any indication of multicollinearity in our models.

TABLE 2: Negative Binomial Regress Estimate of Firm Learning in R&D Alliances

	Firm post-alliance learning (DV)					
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Knowledge domain distance (H1)		-1.161***	-2.054***			-1.370**
		(0.170)	(0.650)			(0.585)
Firm’s knowledge breadth			2.174***			0.212
			(0.677)			(0.653)
Firm's knowledge breadth* Knowledge domain distance (H2)			1.435*			0.934
			(0.740)			(0.716)
Knowledge architecture distance (H3)				5.289***	-0.115	-2.580
				(1.041)	(2.154)	(1.972)
Knowledge architecture distance square (H3)				-8.165***	-7.139***	-5.735***
				(1.749)	(1.584)	(1.790)
Firm's knowledge decomposability					3.000***	2.075***
					(0.286)	(0.477)
Firm's knowledge decomposability* Knowledge architecture distance (H4)					4.991**	6.429***
					(2.102)	(2.025)
Focal firm controls:						
Firm pre-alliance learning (lagged Y)	0.00172***	0.00155***	0.00163***	0.00168***	0.00171***	0.00171***
	(0.000500)	(0.000509)	(0.000458)	(0.000504)	(0.000455)	(0.000311)
Firm's pre-alliance total in-scope patents	0.000616	0.000327	0.000263	0.000394	4.08e-05	-6.25e-05
	(0.000454)	(0.000430)	(0.000406)	(0.000619)	(0.000546)	(0.000501)
Firm's pre-alliance total patents	0.000191***	0.000220***	6.25e-05	0.000192**	0.000137**	0.000121
	(7.07e-05)	(7.25e-05)	(6.55e-05)	(7.81e-05)	(6.74e-05)	(8.17e-05)
Firm's degree of centrality	101.7***	96.90***	72.97***	100.6***	70.83***	71.21***
	(26.56)	(25.45)	(24.58)	(25.24)	(22.89)	(22.60)
Firm's semiconductor industry dummy	0.580***	0.476***	0.673***	0.646***	0.670***	0.632***
	(0.158)	(0.155)	(0.150)	(0.159)	(0.143)	(0.161)
US firm dummy	-0.181	0.0236	0.0769	-0.130	-0.0901	0.00636
	(0.137)	(0.142)	(0.148)	(0.139)	(0.137)	(0.163)
Firm government-related dummy	-2.388***	-2.576***	-2.543***	-2.054***	-2.248***	-2.336***
	(0.699)	(0.551)	(0.488)	(0.710)	(0.673)	(0.538)
Partner firm controls:						
Partner’s pre-alliance total in-scope patents	0.000364	8.51e-05	0.000180	0.000657	0.000839	0.000568
	(0.000470)	(0.000435)	(0.000425)	(0.000610)	(0.000578)	(0.000476)
Partner's pre-alliance total patents	-4.52e-06	-4.70e-05	-6.27e-05	-7.65e-06	-7.31e-05	-5.44e-05
	(6.90e-05)	(6.78e-05)	(6.09e-05)	(6.45e-05)	(5.40e-05)	(6.80e-05)
Partner's degree of centrality	40.16*	19.99	37.10*	31.51	29.01	30.84
	(21.80)	(21.32)	(21.45)	(20.21)	(18.40)	(21.18)
Partner's semiconductor industry dummy	-0.0786	-0.194	-0.101	-0.000343	-0.00123	-0.0890
	(0.145)	(0.153)	(0.142)	(0.148)	(0.131)	(0.158)
US Partner dummy	0.138	0.264*	0.100	0.179	0.139	0.171
	(0.148)	(0.147)	(0.156)	(0.145)	(0.143)	(0.157)
Partner government-related dummy	-0.484	-0.319	-0.103	-0.431	0.454	0.232
	(0.427)	(0.362)	(0.431)	(0.423)	(0.740)	(0.587)
Partner's knowledge breadth			-0.592**			-0.806*
			(0.276)			(0.443)
Partner’s knowledge decomposability					0.0852	0.399
					(0.206)	(0.387)
Dyadic-level Controls:						
Number of prior alliances btw firms	-0.0133	-0.00865	-0.00647	-0.0147*	-0.0119	-0.0105
	(0.00940)	(0.00911)	(0.00913)	(0.00875)	(0.00791)	(0.00865)
JV dummy	-0.494**	-0.542***	-0.595***	-0.527**	-0.605***	-0.612***
	(0.219)	(0.205)	(0.195)	(0.213)	(0.197)	(0.201)
Cross border alliance dummy	-0.158	-0.0823	0.0263	-0.226	-0.219*	-0.100
	(0.155)	(0.146)	(0.152)	(0.142)	(0.131)	(0.156)

Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.873***	3.997***	2.829***	3.622***	0.726	1.807*
	(0.718)	(0.648)	(0.728)	(0.511)	(0.542)	(0.966)
Observations	556	556	556	556	556	556
Log Likelihood	-3209	-3192	-3155	-3199	-3135	-3127
Degree of Freedom	28	29	32	30	33	37
Wald's chi square	505.24	663.59	907.87	635.77	1093.49	531.85
α (dispersion parameter)	2.656***	2.521***	2.247***	2.572***	2.107***	2.061***
Condition number |Mean VIF	14.35|2.98	14.64|2.90	19.51|2.80	14.99|2.96	16.68|2.79	25.38|3.06

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

negative association in Hypothesis 1. The coefficient was positive but insignificant, and the slope tests at the higher and lower ranges of *Knowledge domain distance* were insignificant, rejecting the possibility of a quadratic relationship. The coefficient (Model 2: β = -1.161, SE = .170, p = 0.000) suggest that a one standard deviation increase in *Knowledge domain distance* between firms decreases the cross citation between firms by a considerable factor of 68% ($= e^{-1.161} - 1$), while holding all other variables in the model constant.

In Model 3, the interaction of *Firm's knowledge breadth* and *Knowledge domain distance* on *Firm learning* (H2) is tested. The coefficient (Model 3: β = 1.435, SE = .740, p = 0.053) is positive and marginally significant, supporting H2 that the negative association between knowledge domain distance and firm learning is weakened by firm's knowledge breadth. However, prior studies suggest that in nonlinear models such as negative binomial models, the significance of the interaction term should be interpreted with caution to conclude whether or not the interaction hypothesis is supported (Bowen, 2012; Wiersema & Bowen, 2009). An interaction model in nonlinear models confound two distinct moderating effect: the model inherent moderation which is a function of the model nonlinearity, and the product term which is a function of interaction variables in the model (Bowen, 2012). To this end, we distinguished the model inherent moderation from the product term induced moderation and use the latter one for our interpretation. As illustrated in Fig. 3a, the (total) average marginal effect (AME) of *knowledge domain distance* decreases with *Firm's knowledge breadth*, demonstrating a negative interaction effect of *Firm's knowledge breadth* and *Knowledge domain distance* against our prediction in H2. However, when we partition the interaction components, it appears that negative effect of inherent interaction outweighs the positive effect of product term interaction (Fig. 3b). Excluding the inherent moderation, the (real) average marginal effect (AME) of *knowledge domain distance* increases with *Firm's knowledge breadth* (Fig. 3c). In other words, the effect of *Knowledge domain distance* on *Firm learning* becomes less negative as *Firm's knowledge breadth* increases, supporting H2.

The results in Model 4 support the hypothesized inverted-U shape relation between *Knowledge Architecture Distance* and *Firm learning* in H3. *Knowledge architecture distance* is positive (Model 4: $\beta = 5.289$, SE = 1.041, p = 0.000) and *Knowledge architecture distance squared* is negative (Model 4: $\beta = -8.165$, SE = 1.749, p = 0.000). The slope test at the lowest range is positive and significant ($\beta = 5.289$, SE = 1.041, p = 0.000) and at the highest range is negative and significant ($\beta = -51.167$, SE = 11.294, p = 0.000). In addition, the turning point at which *Knowledge architecture distance* begins to exhibit a negative effect on firm learning occurs at 0.324 ($\beta = 0.324$, SE = 0.044 , p = 0.000), within the data range (0, 1), and 78.8 percent of observations have *Knowledge architecture distance* values below that level. All confirms a quadratic relation in which firm learning increases with knowledge architecture distance and hits its maximum at the 79^{th} percentile of architectural distance range, but this positive association turns to be negative after this turning point.

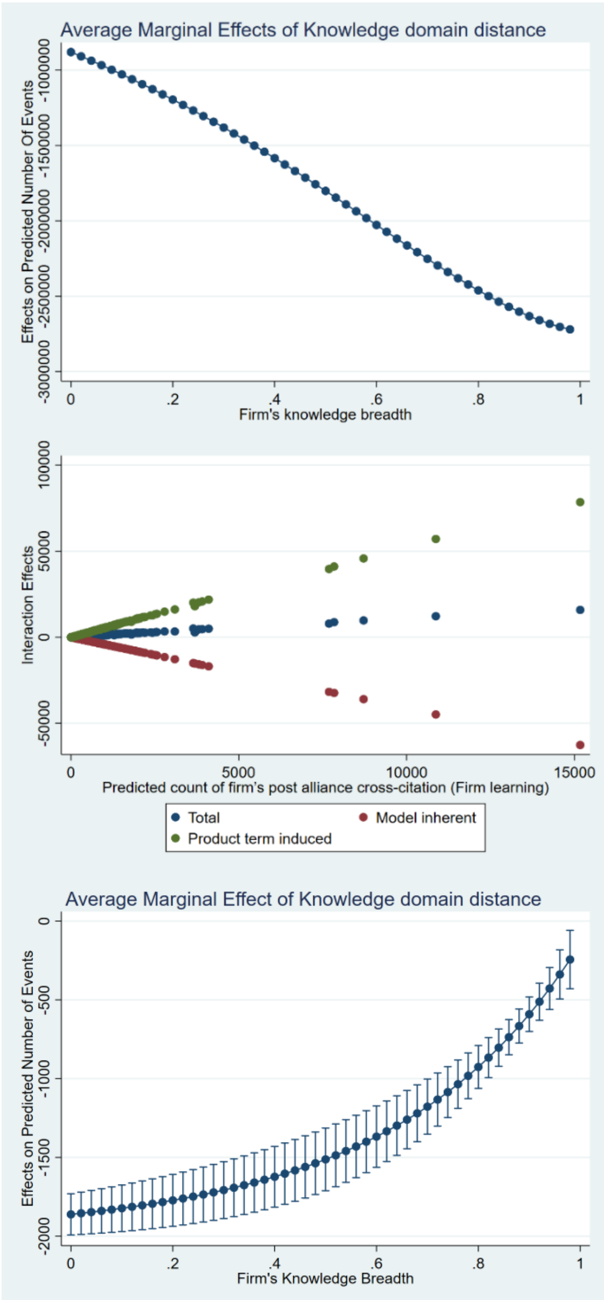
In Model 5, we tested the interaction of *Firm's knowledge decomposability* and *Knowledge architecture distance.* The results confirm H4, as it shows a significant positive interaction between *Firm's knowledge decomposability* and *Knowledge architecture distance*. It suggests that *Firm's knowledge decomposability* shifts the turning point of quadratic relation between *Knowledge architecture distance* and *Firm Learning* to the right (Fig. 4). It is worthy

FIGURE 3:

(a) Average marginal effect (AME) of Knowledge domain distance as Firm's knowledge breadth changes without exclusion of model inherent effect (top).

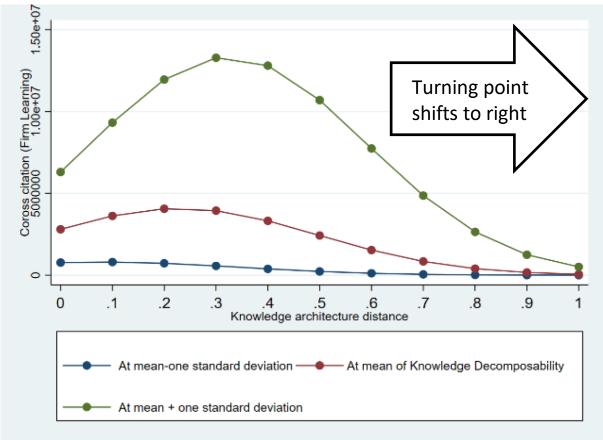
(b) Model inherent, product term induced, and total interaction of Knowledge domain distance and Firm's knowledge breadth on Firm learning (Middle).

(c) Average marginal effect (AME) of Knowledge domain distance on Firm learning as Firm's knowledge breadth changes after the exclusion of model inherent effect (bottom).



to note that the flattening in this figure is an artifact of the nonlinear model as it explained above (Bowen, 2012). The model only includes the linear-by-linear interaction term between *Firm's knowledge decomposability* and *Knowledge architecture distance* as we only address the turning point of the relationship between *Knowledge architecture distance* and *Firm learning* in our hypothesis (Haans et al., 2016; Oriani & Sobrero, 2008). Nevertheless, we also tested the model by including the linear-by-quadratic interaction term between *Firm's knowledge decomposability* and *Knowledge architecture distance squared*, but it did not exhibit statistically significant coefficients, consistent with our expectations.

FIGURE 4: Turning point shift of relationship between Knowledge architecture distance and Firm learning as the degree of Knowledge decomposability increases.



In model 6, we included all main effect and interaction variables. The model supports our H1 and H4. Regarding H2, the coefficient of the interaction between Firm's knowledge breadth and Knowledge domain distance is positive as expected but not significant. Regarding H3, while the expected quadratic relationship between Knowledge architecture distance and Firm learning is still supported, the coefficient of Knowledge architecture distance turns to negative and is not significant. However, these coefficients only indicate the Knowledge architecture distance-Firm learning relationship when the moderator, Firm's knowledge decomposability, is set to zero, which is a very special case, and as the quadratic form of H3 remains, the provided support for H4 is still warranted. The non-linearity of model and the limited number of observation, as a limitation of this study, may explain these relatively weaker results in this model.

Robustness Checks

We took several steps to ensure that our findings are robust. We used alternative estimation models and analysis to make sure the indicated interaction effects is not a natural outcome of negative binomial regression models. We used Poisson regression and OLS regression on the log-transformed version of model to confirm the significance of the interaction effect. All these analyses produced similar and consistent results, thus leading credence to the findings.

DISCUSSION

This study revisits the knowledge antecedents of inter-firm learning in R&D alliances and complements this long stream of research (Inkpen & Tsang, 2007; Kavusan et al., 2016; Lane & Lubatkin, 1998; Mowery et al., 1996; Nooteboom et al., 2007; Sampson, 2007). Extant research has focused on knowledge domain distance to examine the influence of cognitive distance in inter-firm learning. We widened this approach by reconceptualizing cognitive distance based on two dimensions: knowledge domain distance and knowledge architecture distance. We particularly argued that the established inverted-U shape hypothesis between cognitive distance and firm learning is theoretically sound, but this relation is hold in undertheorized knowledge architecture dimension rather than knowledge domain dimension. Our findings confirm that knowledge domain distance has a negative effect on firm learning, though firm's knowledge breadth alleviates this negative effect. We also found that knowledge architecture distance between firms has an inverted U-shape relation with firm learning in alliances. That is, the maximum firm learning occurs at an optimal level of knowledge architecture distance. However, firm's knowledge decomposability, which represents the firm's capacity for change, sets this optimal level. More knowledge decomposability, more capacity to learn from partner firms with greater knowledge architecture distance.

The arguments and findings in this paper have several significant theoretical implications. First, the distinction between knowledge domain and knowledge architecture distance contributes to our understanding of the cognitive distance concept and brings all alternative proposed concepts to address knowledge distance between firms under one umbrella. Second, our approach distinguishes between two inter-firm learning opportunities: learning from within-domain and between-domain knowledge. Our findings demonstrate this distinction, question prior findings, and show that firms can mainly learn from their counterparts' between-domain knowledge rather than within-domain knowledge in R&D alliances. In other words, our findings highlight the role of an R&D alliance as a proper vehicle to change the cognitive map and problem-solving attitudes of alliance partners, rather than the extension of their knowledge domains.

Third, our findings criticize the stylized findings in literature with respect to the benefit of knowledge domain distance. One possible reason for this disparity is in the way that extant research operationalizes the concepts of knowledge domain distance and firm learning. These studies generally take all the registered patents of firms into account that significantly distort to the measures. For example, knowledge domain distance between a large diversified firm and a small firm is typically greater than the domain distance that operates in their alliance with limited scope, because the knowledge base of the larger firm includes multiple ex-scope knowledge domains absent in the knowledge base of its smaller counterpart that exaggerates knowledge domain distance. Moreover, the number of post-alliance patents in large firms may increase because of their investment in ex-scope domains. To this end, we took special care of the technological scope of alliances to significantly improve the precision of our analysis. Our approach in the identification of the technological scope of alliances is novel. We analyzed the technical content of each alliance agreement and took that part of a firm's knowledge into account that has fallen in the knowledge category of alliance technological scope or has been used by its association. This approach minimizes the noise of attributing knowledge domains to the alliances that have never been used or created in alliances, particularly in large companies that have a very wide knowledge breadth and use different knowledge sourcing instrument (Sampson, 2007). This approach can be widely applied to research on firms' activities within specific technological scope; machine learning techniques can particularly improve and standardize it.

This study also has important managerial implications. Firms may choose different knowledge sourcing strategies to enrich their knowledge bases (Bierly & Chakrabarti, 1996; Hagedoorn, 2002; Hagedoorn & Duysters, 2002). We identify two distinct dimensions of firm's knowledge base and redefine the boundaries of R&D alliances with respect to these dimensions. Our findings suggest that an R&D alliance is a proper choice for firms seeking to renew their knowledge architectures, rather than to extend their knowledge domains. Prior studies show that firms face difficulty in the renovation of their knowledge architecture, while it is an important source of architectural innovations (Henderson & Clark, 1990; Yayavaram & Ahuja, 2008).

Naturally, this research has several limitations. First, the alliances examined in this study are those pertaining to R&D alliances, and although our argumentation is general and can apply to learning in all types of alliances, we should be cautious in the generalizing our findings to the other types of alliances (e.g., marketing, manufacturing, and supply chain). Second, we used patents to develop our main measures; however, the accuracy of patents to represent firm's knowledge and inter-firm learning is under question (Roach & Cohen, 2013). Nevertheless, our treatment in specifying the scope of alliance offers a solution to use patent data in a more precise way to measure innovative performance of firms. Third, learning is a multifaceted construct and measuring the learning in technological aspect may not represent the realized learning in alliances. However, we tried to partially address this issue by narrowing our sample selection strategy to the R&D alliances that explicitly specified their research agenda.

Future research may extend this study in both theoretical and empirical aspects. From the theoretical point of view, we distinguish between two inter-firm learning opportunities. This approach invites future research to revisit knowledge sourcing strategies of firms accordingly. This study mainly suggests that R&D alliances are mainly proper vehicles for learning knowledge architecture rather than knowledge domain. Future studies may examine the other forms of knowledge sourcing such as M&A with this respect: which knowledge-sourcing mode provides which learning opportunity.

Prior literature suggests repetitive alliances, at least to a certain level, may improve the chance of learning. We controlled for the number of prior-alliances in this study. However, future research may examine whether learning opportunities from knowledge domain distance appear in the repetitive alliances between the same firms or within the same technological scope. Future studies may also consider a combination of inter- or intra- organizational activities in knowledge sourcing regarding both dimensions, separately or together. Moreover, further research may also study alliance portfolios to examine how a combination of different alliances jointly influence firm's knowledge base.

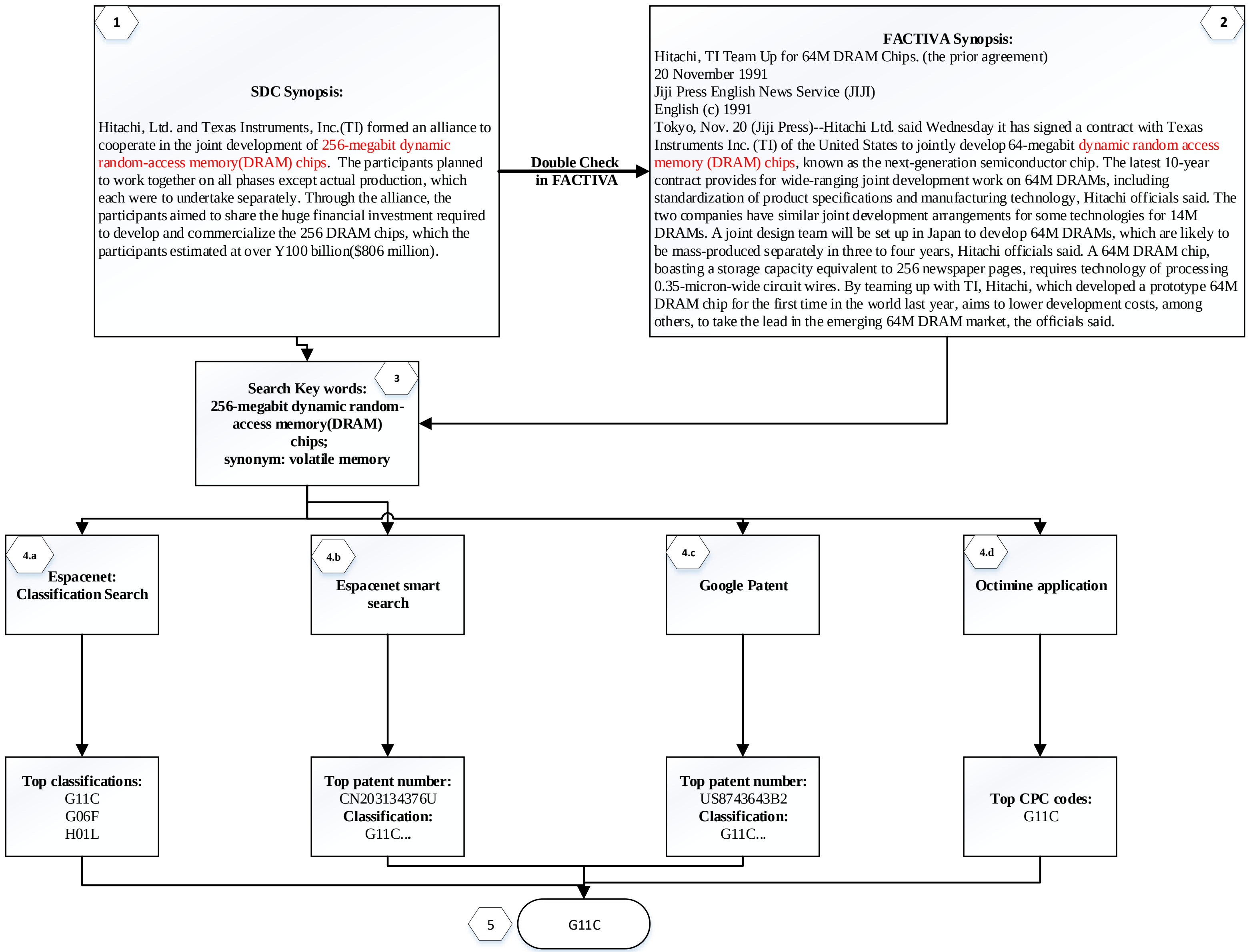
This study exclusively focuses on firm learning in R&D alliance. There are opportunities to use our approach to extend research on the alliance scope and the trade-off between firm's performance and alliance performance (Khanna, 1998; Khanna et al., 1998). For example, future studies may examine firm learning, as a firm-level benefit, against alliance performance, as an alliance-level benefit, in the same setting to delineate the trade-off between these two essential outcomes. Finally, future research may use our approach in the identification of alliance technological scope to examine the trade-off between the breadth of alliance technological scope and firm learning with respect to each dimension.

APPENDIX 1

We followed the below procedure to match the technological scope of alliance agreement with patent sub-classes in cooperative patent classification (CPC) scheme.

1) Reviewing the alliance agreement synopsis in SDC database and selecting the technological key words.
2) Double-checking the agreement in FACTIVA database to seek for further information.
3) Choosing the keyword and finding the relevant synonyms.
4) In this step, we search for the patent sub-class in various patent databases simultaneously:
   i. Direct search for patent sub-class in "classification search" option in Espacenet website, a worldwide dataset for patent search, to find the top suggestions.
   ii. Search for patent in "smart search" and "advanced search" options in Espacenet to find the most relevant patents, and to identify the patent sub-class of the found patent after checking the title and abstract of patent.
   iii. Doing the same procedure in Google Patent database
   iv. Using Octamine application, a private patent search engine, to find the top patents and top patent-subclasses to double-check the finding in the above procedure.

We use the example that we used in this paper (i.e., R&D alliance agreement between Hitachi and Texas Instrument (TI) to develop Dynamic random memory (DRAM)) to illustrate the process in below flowchart.


1
SDC Synopsis:
Hitachi, Ltd. and Texas Instruments, Inc.(TI) formed an alliance to cooperate in the joint development of 256-megabit dynamic random-access memory(DRAM) chips. The participants planned to work together on all phases except actual production, which each were to undertake separately. Through the alliance, the participants aimed to share the huge financial investment required to develop and commercialize the 256 DRAM chips, which the participants estimated at over Y100 billion($806 million).
Double Check in FACTIVA
2
FACTIVA Synopsis:
Hitachi, TI Team Up for 64M DRAM Chips. (the prior agreement)
20 November 1991
Jiji Press English News Service (JIJI)
English (c) 1991
Tokyo, Nov. 20 (Jiji Press)--Hitachi Ltd. said Wednesday it has signed a contract with Texas Instruments Inc. (TI) of the United States to jointly develop 64-megabit dynamic random access memory (DRAM) chips, known as the next-generation semiconductor chip. The latest 10-year contract provides for wide-ranging joint development work on 64M DRAMs, including standardization of product specifications and manufacturing technology, Hitachi officials said. The two companies have similar joint development arrangements for some technologies for 14M DRAMs. A joint design team will be set up in Japan to develop 64M DRAMs, which are likely to be mass-produced separately in three to four years, Hitachi officials said. A 64M DRAM chip, boasting a storage capacity equivalent to 256 newspaper pages, requires technology of processing 0.35-micron-wide circuit wires. By teaming up with TI, Hitachi, which developed a prototype 64M DRAM chip for the first time in the world last year, aims to lower development costs, among others, to take the lead in the emerging 64M DRAM market, the officials said.
3
Search Key words:
256-megabit dynamic random-access memory(DRAM) chips;
synonym: volatile memory
4.a
Espacenet: Classification Search
4.b
Espacenet smart search
4.c
Google Patent
4.d
Octimine application
Top classifications:
G11C
G06F
H01L
Top patent number:
CN203134376U
Classification:
G11C...
Top patent number:
US8743643B2
Classification:
G11C...
Top CPC codes:
G11C
5
G11C

CHAPTER 3

MULTI-PARTNER R&D ALLIANCE DIVERSITY AND INNOVATION PERFORMANCE:
THE DILEMMA OF VALUE CREATION AND VALUE APPROPRIATION

ABSTRACT

We systematically examine partner diversity in multi-partner alliances and its performance consequences both at the alliance level as well as at the firm level in the context of technological knowledge sourcing. We identify three dimensions of multi-partner diversity, namely partner variety, relational separation, and status disparity, based on within-firm, between-firm, and across the entire network resources, respectively. We argue that each of these dimensions has distinct performance consequences at alliance and firm levels. We tested our theory on a sample of research and development collaborations in technology-driven industries from 1990 to 2008. Our findings reveal diverging mechanisms of value creation at the alliance level and value appropriation at the firm level regarding each dimension of multi-partner alliance diversity. Our results suggest that managers should be cautious with configuring multi-partner alliances and consider the critical trade-offs between value creation and value appropriation when they are deciding to join, stay, or leave multi-lateral partnerships.

Keywords: *multi-partner R&D alliance; multi-partner diversity; value creation; value appropriation*

INTRODUCTION

Multi-partner alliances (MPAs) have gained popularity in technology-driven industries due to the speed of technological advancements, the competitive pressure to set the next technological standards, and the complexity of problems to solve. Firms voluntarily engage in MPAs in multilateral value chain activities to take advantage of their complementary resources and capabilities, to access valuable information, to share the costs and risks of undertaking exploratory and uncertain activities, to shorten the product lifecycle, and to improve their collective competitive advantage (Lazzarini, 2007; Das & Teng, 2002; Lavie et al., 2007; Gomes-Casseres, 2003). MPAs appear in different forms such as R&D consortia, multiparty production bundling, supplier networks, joint bidding, and industry constellations (Das & Teng, 2002; Li et al., 2012; Ekeh, 1974; Lavie et al., 2007). MPA setting is a unique phenomenon in interorganizational relations (IORs). The received wisdom from sociology suggests that the dynamics of interactions in a group substantially change when a dyadic relation turns to triadic or multilateral relations (Simmel, 1950). Likewise, the dynamics of multi-lateral interaction within a group of firms in MPAs is different from the dynamics of the bilateral interaction between two firms in a dyadic alliance (Das & Teng, 2002). Moreover, the dynamics of such a within-group multi-lateral interaction in the MPA is different from an ego network (alliance portfolio), in which a focal partner firm manages each of its direct relation with its counterparts independently.

IOR researchers have paid more attention to MPA in the last two decades. This stream of research has addressed several organizational attributes of MPAs, such as the governance modes, contractual forms (García-Canal, 1996; Gong et al., 2007; Li et al., 2012), and the cooperative relationships between the MPA partners (Das & Teng, 2002; Heidl et al., 2014; Madhavan et al., 2004); strategic decisions throughout its lifecycle, such as decisions about joining, staying in, or leaving an MPA (Olk & Young, 1997; Lavie et al., 2007, 2015), and the benefits of membership in an MPA (Gomes-Casseres, 2003; Lazzarini, 2007). However, these studies have paid relatively less attention to MPA as an organizational association or a strategic entity (Das, 2015; Gomes-Casseres, 2003; Lavie et al., 2007). Consequently, our knowledge about the antecedents of group based advantages of MPAs in value creation, the aggregated performance of an MPA partners as the MPA performance, and the internal dynamics that shape what a partner firm can appropriate from these advantages, the partner firm performance, is relatively limited.

Strategic management literature suggests that one of the main factors that can explain the performance of such an organizational association or a strategic entity with multiple sub-entities is the diversity or the distribution of differences among its members with respect to a common attribute (for a recent review see Ahuja & Novelli (2017)). IOR researchers have studied the diversity of partner firm’s resources in dyadic alliances (Sampson, 2007) and of partner firms in alliance portfolios (Jiang et al., 2010). However, the diversity of MPAs has mainly remained unexplored. Exploring MPA diversity can improve our understanding about the antecedents of overall performance of an MPA and of its partner firms, and in consequence, the rationale behind the choice of firms in forming or joining, staying, and leaving an MPA. The diversity of an MPA can be defined based on different attributes of its partner firms, so it necessitates a systematic approach to study the different possible dimensions of diversity and their performance consequences. Moreover, the performance consequences of MPA diversity at alliance and firm levels are not necessarily aligned, as the mechanisms and dynamics of value creation at the MPA-level are not necessarily compatible with the mechanisms of value appropriation at the firm level. However, IOR research has mainly overlooked this critical point. For instance, Lee, Kirkpatrick-Husk, and Madhavan (2014) show in their meta-analysis that the performance consequences of alliance portfolio diversity are neither theoretically clear nor empirically consistent, as existing studies tend to overlook the fundamental difference of diversity and performance at different levels of analysis.

In this study, we systematically examine the relation between MPA diversity and performance. We submit that an MPA is a multifaceted phenomenon that cannot be simply explained in a single dimension, as participating firms join MPAs with different attributes in terms of their internal resources and capabilities, their relational resources with their counterparts in MPA, and their status in the global alliance network. To this end, we dimensionalize the MPA diversity construct with respect to partner firms' attributes and resources within-firm, 'partner variety', between-firm, 'relational separation', and across the entire network, 'status disparity'. We separately examine the performance consequence of each dimension at the MPA level as well as the firm level.

We argue that diversity in each of these dimensions has an inverted U-shaped relation to MPA performance. Partner variety provides the MPA with more opportunities and resources to achieve its intended goal, but as the MPA's diversity in this dimension exceeds a certain point, MPAs' ability to exploit these opportunities sharply decreases. Likewise, moderate relational separation among partner firms may benefit MPA, as partner firms may learn from novel procedures and ideas from the partner firms that they had less interaction before, but excessive relational separation may lead to dividedness in the MPA and may hurt the alliance performance. Finally, while status disparity may ease coordination via higher status firms to a certain level and benefit MPAs to a certain level, the inequality across MPAs with high disparity can disturb the required transparent multilateral interaction for efficient collaboration among the alliance partners, exerting a negative effect on MPA performance.

At the firm level, however, we argue that the performance consequence of each diversity dimension is not consistent with that at the MPA level. Partner firms with lower internal knowledge variety, or in the other words, with narrower knowledge breadth, do not benefit from partner variety as much as their counterparts with broader knowledge do. With respect to relational separation and status disparity, likewise, partner firms with a brokerage role in divided partnerships, as well as those with high status in the global alliance network can extract a higher share of value created by the MPA.

We examine our theory in the context of technological collaboration, focusing on R&D consortia in high-tech sectors including electronic and computer components producers, telecommunication equipment and system providers, medical equipment producers, and firms from the pharmaceutical industry. The rationale behind this choice is that these industries regularly practice multi-lateral partnership for their technology-based activities. We compiled a sample of multi-partner R&D collaborations from the SDC platinum data set, enhanced by FACTIVA, and combined with the patent data extracted from PATSTAT by matching assignee names of granted patents to firm names of the MPA sample. Then, to have more precision for the patent-based dependent variables, we established the technological scope of each alliance by carrying out an elaborate content analysis on the alliance's technological description to code their technological domain based on the patent classification index. We test our hypotheses at two distinct levels of MPA and partner firms. Overall, our findings are consistent with our main arguments that the performance consequences of multi-partner alliances vary between the distinct dimensions of MPA diversity. Specifically, our results underline the distinction between underlying mechanisms of value creation at the MPA level and value appropriation at the firm level.

To our knowledge, this study is the first to distinguish systematically the different dimensions of MPAs and to examine the performance consequences of each dimension at both the alliance and firm levels. It offers a novel insight into the conceptual meaning of MPA diversity and its performance consequences. We believe that this approach may contribute to our understanding of performance consequences of diversity in the general strategy literature, as diversity is such an important construct in a wide range of contexts. The findings contribute to our understanding of the complex configuration of MPAs. They particularly underline the distinct dynamics of alliance and partner firm performance in MPAs. There are critical trade-offs to be considered by partner firms in their decision to join, stay, or leave multi-partner alliances.

MULTILPLE-PARTNER ALLIANCE DIVERSITY: THE DIMENSIONS

"A multi-partner alliance is a collective, voluntary organizational association that interactively engages its multiple members in multilateral value chain activities, such as collaborative research, development, sourcing, production, or marketing of technologies, products, or services" (Lavie et al., 2007, p. 578). Multilateral interaction within a group of firms as an organizational association are the distinctive characteristics of an MPA. They distinguish an MPA from the bilateral interaction between two firms in a dyadic alliance, from a portfolio of independent bilateral interactions between partner firms and a focal firm in an alliance portfolio, and from a network of bilateral interactions among different firms in an alliance network. These unique characteristics necessitate a different framework that explains the source of group based advantages of an MPA and that explains how the within-group multi-lateral interaction in an MPA shapes what a partner firm can appropriate from its group work (Gomes-Casseres, 2003, p. 333). The received wisdom from the diversity research in strategic literature suggests that one of the main factors that can explain the performance of such an organizational association as a strategic entity is its diversity or the distribution of differences among its members with respect to a common attribute.

In an MPA, the differences among the MPA partners with respect to their resources can be a source of group-based advantages of MPAs to fulfill their intended goals. In addition, these differences can also determine the advantage of some partner firms in appropriating more value than their counterparts from the total created value. The partner firms join an alliance with their internal resources within their organizational boundaries, with their relational resources based on prior relations with their counterparts in the MPA, and with their social capital based on the status that they have acquired in the global alliance network. We argue that MPA diversity can be dimensionalized with respect to these within-firm, between-firm, and across the entire network resources, as each reflects a distinct attribute of partner firms and can be a source of value creation in MPA as well as value appropriation by partner firms.

Firms share their distinct knowledge, information, and resources in alliances to fulfill their common goals. The development path of these resources is idiosyncratic (Nelson & Winter, 2009) that implies uniqueness or distinctiveness of these resources. Group diversity research uses the term of variety to refer to differences in kind, source, or category of background and associated experience among group members (Harrison & Klein, 2007; Van Knippenberg & Schippers, 2007). Likewise, we label diversity in this dimension as partner variety that refers to the qualitative difference of partner firms on a categorical attribute such as their functional backgrounds, knowledge, information, and resources. Partner firms with unique and distinct attributes provide their partnerships with the maximum partner variety; in contrast, the minimum partner variety occurs when all partner firms share similar attributes.

Partner firms also bring their between-firm relational resources to MPAs. Each couple of firms in an MPA might have developed varying levels of bilateral trust and mutual understanding on their prior relations. These relational resources can represent the proximity of organizational attitude and approaches toward various aspects of partnerships. The difference in the strength of between-firm relational resources can potentially divide an MPA into cohesive subgroups of partner firms, because of mistrust, and conflict in their attitudes and approaches to their collaboration (Heidl et al., 2014). Group diversity research labels this type of diversity that represents the differences in lateral position or opinion among group members (e.g., different values, beliefs, or attitudes of partners) as separation, implying disagreement or opposition among them (Harrison & Klein, 2007; Van Knippenberg & Schippers, 2007). Likewise, we name diversity in this dimension as relational separation. Relational separation refers to the members' differences in terms of a single continuous attribute such as commitment, trust, or belief in the goal of collaboration that affects the cohesion between them and leads to a set of systematic consequence. The highest degree of separation occurs when partner firms are divided into two subgroups, each taking a stance as far from the other as possible; in contrast, the minimum relational separation occurs when all partner firms practice similar approach in their partnership and form a single cohesive group.

Network resources, or the social capital of partner firms, can also be a source of diversity. While relational resources refer to prior ties between partner firms within an MPA, network resources brought in by a partner firm are accumulated from the entirety of its past relations, not just those relations with partner firms of the focal MPA. Social capital can provide firms with credit, privileged access to information, opportunities, and reputation or status (Nahapiet & Ghoshal, 1998; Granovetter, 1985). According to social network theory the centrality position of an entity, as a particular node in the global network, can reflect its social status (Bonacich, 1987). Likewise, the centrality position of a partner firm in its global networks can provide access to information through direct and indirect ties, and being in the different possible paths of information provides firms with this chance to influence the information flow between the other firms in the network. It is assumed in this dimension that members can be different in the degree to which they possess specific attributes that also implies their prestige, quality and income (Gnyawali & Madhavan, 2001). Group diversity research names this type of diversity as disparity (Harrison & Klein, 2007; Van Knippenberg & Schippers, 2007), and we label it as status disparity in this context. Multi-partner alliances in which the status of one firm outranks the others has the maximum disparity, because the high-status firm can dominate the MPA; in contrast, minimum diversity occurs when all firms are in the same status, either low or high. It should be considered that the disparity dimension is asymmetric by nature. For example, if all partner firms have high status except one, the disparity would be low, because in this case just one firm is disadvantaged relative to the majority, but when just one firm has high status, the disparity would be high, because the majority of partner firms disadvantaged relative to the privileged one.

It is worthy to note that the overall size of an MPA (i.e., the number of partner firms) does not address "within-unit" types of diversity. In addition, prior research has shown that the advantage of a multi-partner alliance is in fact not so much determined by its size, but by certain characteristics and quality of the partner firms and their interrelations (e.g., Stuart, 2000).

THE ALLIANCE & PARTNER FIRM PERFORMANCE IN MULTIPARTNER ALLIANCES

Strategic alliance research suggests that partner firms not only collaborate to create value at the alliance level but also compete to appropriate more value than their counterparts in their partnerships (Dyer et al., 2008; Adegbesan & Higgins, 2011; Hughes-Morgan & Yao, 2016; Lavie, 2007; Lee et al., 2014; Hamel, 1991). Therefore, not all partners may be able to proportionally benefit from the produced collaborative rent from shared resources. Moreover, value appropriation entails not only the partner’s share from the common benefits, or benefits to all parties based upon the alliance’s specific objectives, but also the partner’s private benefits or gains that are realized only by individual firms in the alliance (Khanna et al., 1998). We distinguish between the value creation mechanism, leading to the alliance performance, and the value appropriation mechanism, leading to the partner firm performance to have a better understanding of the group-based advantages and the within-group interactions of MPA. In the following, we separately examine the performance at the MPA level and at the firm level with respect to each dimension of diversity.

Value Creation at MPA level

Partner variety

The most explored dimension of diversity in alliances is partner variety. Extant studies show that variety in terms of partners' differences in their resources, knowledge, information, or experience are a prevalent rationale for creating multiple alliances (Baum et al., 2000; Das & Teng, 2002; Ozcan & Overby, 2008; Sakakibara, 1997b).

A diversified MPA in partner variety dimension can benefit from the critical and complementary resources and capabilities to achieve fuller utilization of partner firms' resources, create more synergy and added value, and to hedge the risks of undertaking uncertain activities (Lazzarini, 2007; Ozcan & Overby, 2008; Sakakibara, 1997a, 2001; Xu et al., 2014). The variety of knowledge and problem-solving capabilities, as well as the spread of non-redundant knowledge across partner firms enable the partnership to explore novel opportunities and find more creative solutions for their common problems (Olk & Young, 1997).

However, such an opportunity comes at a cost. When the difference between partner firms' shared resources increases, the mutual understanding and relational absorptive capacity to assimilate and recombine their shared resources decreases (Sampson, 2007; Lane & Lubatkin, 1998; Mowery et al., 1996). In the context of MPAs, this undesired effect can be even stronger as the mutual understanding and relational absorptive capacity among multiple partners decrease faster with partner variety.

Therefore, as partner variety increases the difficulty of its utilization increases in a way that after a certain point outweighs its benefits, so we expect that partner variety bears a nonlinear relationship with innovative performance of MPAs.

Hypothesis 1: Multi-partner R&D alliances with moderate partner variety has higher innovation performance (create more value) than alliances with very low or very high levels of partner variety.

Relational Separation

As discussed earlier the separation type of diversity refers to the difference in opinions, beliefs, and cognitive processes among the members. Extant studies suggest that partner firms who are strongly tied to each other are more likely to develop a shared understanding and closer opinions and beliefs to reinforce their existing relationships and facilitate the exploitation of shared knowledge bases (Beckman et al., 2004; Verspagen & Duysters, 2004). That is, engaging in recurrent alliances with a select group of partner firms can influence their cooperative behavior (Gulati, 1998), diminish exchange hazards and promote trust (Gulati & Nickerson, 2008), and improve the chance of effective coordination across partner firms to facilitate the flow of knowledge and information and complete their joint and individual tasks (Gulati et al., 2012).

Hence, as the variation of tie strength between a group of partner firms based on their prior interactions increases, fragmented subgroups, which are cohesive within but cannot effectively interact between, emerges (Heidl et al., 2014; Gibson & Vermeulen, 2003). Such polarization leads to more conflicts, reduces the cooperative motivation of partner firms, and damages the embedded relation between these subgroups, so the expected synergy, coordination, cooperative culture, and the performance of working with a group of partners diminishes (Das & Teng, 2002).

Nevertheless, having new partners with no prior ties, implying the difference in opinions and cognitive processes in this context, can lead to productive conflict specifically in research collaborations. In addition, new partners can provide MPAs with new information channels, different perspectives, and new knowledge that are not available through existing immediate network (Lavie & Rosenkopf, 2006), increasing the chance of finding novel ideas and more creative solutions.

In sum, as relational separation increases the access to new information channels and knowledge resources increases, but the cooperative culture of MPAs decreases in a way that after a certain point outweighs its benefits. Thus, we expect that relational separation bears a nonlinear relationship with innovative performance of MPAs.

Hypothesis 2: Multi-partner R&D alliances with moderate relational separation has higher innovation performance (create more value) than alliances with very low or very high levels of relational separation.

Status disparity

Network research shows that the firm's structural position, centrality, comes with status and social power (Bonacich, 1987; Gulati et al., 2000; Nahapiet & Ghoshal, 1998; Stuart & Sorenson, 2007). As firms develop more central network positions, they accrue resource and information benefits that enhance their ability, social power, and so their performance (Powell et al., 1996; Shipilov & Li, 2008). In addition, firms with central positions in the global network are particularly able to achieve the benefits of ties to prominent partners, because centrality provides superior information, legitimacy, and prestige, thus improving their negotiation power (Bae & Garguilo, 2004).

Status disparity addresses the difference of partner firms' status in the global alliance network. Status disparity implies that at least one partner firm has higher status than its counterparts do. Such disparity may benefit MPAs in two ways. First, it provides valuable information, legitimacy, and prestige to the MPA that can benefit all. In addition, powerful, high status partner firms can facilitate coordination across partner firms to align and adjust partners’ actions to achieve jointly determined goals (Gulati et al., 2012, p. 537).

However, high level of status disparity comes with the inequality of the status and asymmetry of social power among partner firms that leads to conflict of interest and disturbs the required transparency for efficient cooperation. This disparity induces high-status firms to their unilateral outcome at the cost of their partners, so the chance of their opportunistic behavior increases (Lavie, 2006, 2007). Low-status firms, in anticipation of such opportunistic behavior by high-status counterparts, will exert less effort towards the MPA. Therefore, even if partner firms have strong intention for collaboration, status disparity induces them to be less transparent and institute protective mechanisms to limit their outbound spillovers, which will dampen the MPA performance.

Therefore, status disparity provides partner firms with accessing superior information, prestige, and legitimacy as well as easing the coordination within MPA, but it harms the cooperation in MPAs in a way that after a certain point outweighs its benefits, so we expect that status disparity bears a nonlinear relationship with innovative performance of MPAs.

Hypothesis 3: Multi-partner R&D alliances with moderate status disparity have higher innovation performance (create more value) than alliances with very low or very high levels of structural disparity.

Value Appropriation at the Firm Level

Diversity in different types of resources has performance consequences at both MPA and firm levels, but their effects on the partner firms’ performance are conditioned by partner firm’s resources. We argue that the mechanism of value creation at MPA-level is not necessarily applicable to value appropriation mechanisms at the partner-firm level, so we do not focus on the main effect of diversity dimensions at MPA-level on the firm-level performance. We focus on the interaction of MPA diversity in each dimension with its corresponding partner firm resources on the proportional value that partner firms appropriate in compare to all MPA.

Partner variety at the MPA level and internal knowledge variation at the firm level

At the firm level, received research shows that getting access to a variety of knowledge and exposure to partners' diverse technologies provides more recombination and reconfiguration opportunities between new knowledge and existing knowledge to come up with more creative solutions (Sampson, 2007; Caner et al., 2017; Srivastava & Gnyawali, 2011). However, the firms' ability to learn and utilize novel knowledge from different types of knowledge sources is a function of their absorptive capacity with respect to each of these new sources of knowledge (Cohen & Levinthal, 1990; Lane & Lubatkin, 1998). The prior related knowledge allows firms to absorb and recombine the created knowledge and resources in their partnerships with their own existing ones (Grant & Baden-Fuller, 1995; Lavie, 2006; Dyer et al., 2008; Kogut & Zander, 1992) and offers them the opportunity to access complementary knowledge and skills to exploit their existing capabilities or to explore novel opportunities (Lavie et al., 2007; Lavie & Rosenkopf, 2006).

In MPAs with a higher variety of knowledge and resources due to the partner variety, partner firms with broader internal knowledge have more chance to appreciate and utilize new knowledge, so they can proportionally appropriate more value than what their counterparts can with limited internal knowledge variety. Therefore, regardless of the relation between partner variety and value creation at the level of the MPA, which is indeed a function of partner variety at MPA level, partner firms' value appropriation from their collective effort diverges to the extent of their differential internal knowledge variety.

Hypothesis 4: MPA partner variety positively moderates the positive relation between the partner firm's internal knowledge variety and partner firm's value appropriation.

Relational separation at MPA-level and brokerage role of firms

At the firm level in a multilateral partnership setting, partner firms who have stronger relations with their counterparts, especially with those who are weakly connected with each other, can enjoy a brokerage role (Ahuja, 2000; Zaheer & Bell, 2005). A brokerage role can provide firms with more diverse and timely information to take advantage of weak ties between counterparts, as well as power and control to play off one counterpart against another (Burt, 2009; Zaheer et al., 2010).

With this respect, a partner firm that has close relations with its counterparts in an MPA with high relational separation has the chance to take advantage of both different novel ideas and perspectives as well as the weak ties between them. Having relations with separated subgroups improve the bargaining power of the focal firm in terms of the possibility of working with both subgroups and of the unique information from both subgroups, giving it the upper hand to appropriate a larger share of created value (Dyer et al., 2008; Lavie, 2006). In this respect, partner firms with more brokerage opportunities take even more advantage of their unique positions in MPAs with deep divisive fault lines (Heidl et al., 2014).

Therefore, it follows that regardless of the relation between relational separation and value creation at MPA, as relational separation increases, particular partner firm(s) can take more advantage of their brokerage role to appropriate more value than what other partners can.

Hypothesis 5: MPA relational separation positively moderates the positive relation between the partner firm's brokerage role and partner firm's value appropriation.

Status disparity at MPA-level and status of firms

At the firm level, a partner firm that has higher status enjoys its superior situation to access critical information, to get the upper hand in the ex-ante negotiations, and to take actions in cooperation that cannot be easily responded by their counterparts (Gnyawali & Madhavan, 2001). In addition, high status partner firm(s) usually take the lead to coordinate the collaboration, so they can influence it in a way to be more consistent with their routines and appropriate more value than their counterparts can.

Therefore, regardless of the relation between status disparity and value creation at MPA, as status disparity increases, particular partner firm(s) can take more advantage of their higher status to appropriate more value than what other partners can.

Hypothesis 6: MPA status disparity positively moderates the positive relation between the partner firm's status and partner firm's value appropriation.

METHODS

Empirical Design and Data

Empirical Design. We tested our theory in the context of research collaboration in a group of high-tech industries. We selected a group of high-tech industries that regularly involve in practice of patenting innovations, and their heterogeneous population provides ample variation to test the hypotheses (Stuart, 2000). In addition, these industries regularly engage in multiple and simultaneous alliances to address different technological requirements and the risks of developing and launching new products. With this respect, we focus on high-tech industries such as pharmaceutical, medical equipment, laboratory, computer, and electronics and communication industries with the following three-digit SIC codes: Drugs (SIC: 283), Computer and office equipment (SIC: 357), communication equipment (SIC: 366), Electronic Components and Accessories (SIC: 367), Laboratory, Optic, Measure, Control Instruments (SIC: 382), Surgical, Medical, Dental Instruments (SIC: 384), Telephone Communications

(SIC: 481), Communication Services (SIC: 489), Computer Programming, Data Processing, etc. (SIC: 737), and Research, Development, Testing Services (SIC: 873).

Data. We collected the alliance data from the JV & Alliance section of SDC Platinum database. We selected the multi-partner R&D alliances that formed between 1990 and 2008 in the aforementioned high-tech industries, considering the SIC-Primary (i.e., SICP) flag of alliances. We identified 155 multilateral R&D alliances after verifying the alliance status (i.e., completion), removing MPAs with undisclosed partners, and comparing the SDC information with the ones in FACTIVA dataset. Finally, we tracked historical alliances (all types of alliances, including dyadic alliances) all the way back to the year 1985 in order to ensure sufficient coverage of active alliances for the required analysis in this study.

We extracted the patents from the EPO Worldwide Patent Statistical Database (PATSTAT[9]). PATSTAT covers all registered patents in more than 100 patent offices that allows us to aggregate the registered patent at patent family level (DOCDB patent family) to cover all the relevant registered patents in different patent offices without over counting those registered in multiple offices. This database, as the NBER and the USPTO patent database, contains patent number, assignee name, filing year, and grant year, but not CUSIP numbers (key identifier used in Compustat & the SDC databases) of the assignee firms, so matching of patents with identified firms in our sample is not straightforward.

Therefore, we took significant care in matching our firm list and patent data. First, we used the company directory list, who-owns-whom information, in LexisNexis to identify all divisions, subsidiaries, and joint ventures of each firm at the level of parent firm in the sample. We then used different online sources to trace each firm's history to account for name changes,

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[9] PATSTAT Edition: 2017 Autumn; Classification Version: 2013.

division names, divestments, acquisitions, and joint ventures; and to obtain precise information on the timing of these events. This process yielded a master list of entities that we used to identify all patents belonging to sample firms during the period of study. To match the corresponding patents to each firm, we first used the name-matching bridge between NBER/USPTO patents and Compustat firms provided by Hall and colleagues (Hall et al., 2001), in which patent assignee names are standardized and matched with firm names in Compustat. However, we could find patent information for all partner firms in our sample, and we could not determine whether the rest of the firms had no patents or had patents but did not appear in this database. In addition, our sample is not limited to the public firms and includes non-public firms which are not recorded in Compustat. Therefore, we wrote a name-matching program to get additional patent for both public and non-public firms in our database. The resulting collected patents were granted between 1985 and 2013 to our sample firms. Finally, we dropped 18 alliances of non-patenting firms, as it was not possible to develop both independent and dependent variable measures, so the final sample of our study consists of 137 multipartner R&D alliances.

As large firms may diversify in different industries and technologies, relying on all their patent data might be misleading in our analysis (Sampson, 2007). To this end, we performed a content analysis of the technological description of each alliance agreement to determine its technological scope. We obtained the technological descriptions from the SDC and FACTIVA. Then, we followed the patent office procedure for examiners to match these descriptions to specific technology sub-classes under the Cooperative Patent Classification (CPC) scheme (*Espacenet - Classification Search*, n.d.; Hunt et al., 2012; White, 2010)[10]. The

[10] https://worldwide.espacenet.com/classification?locale=en_EP

CPC is a common classification system for patent documentation that integrates the USPTO (American system) and the EPO (European System) and classifies technologies in hierarchical nested levels, such as section, class, subclass, and so on (*Cooperative Patent Classification - About CPC*, n.d.). In short, we made a brief, accurate summary of the technological description of each alliance, noted the key technical words, and searched for the synonyms. Then, we used the advanced search form in the EPO search engine, and search keywords and synonyms in the Title and Abstract fields to retrieve a list of the corresponding sub-classes. Finally, we retrieved the corresponding patents to each sub-class and reviewing their abstracts and top claims to check the relevancy of the patents to the technological scope of alliances, this procedure is in accordance with what is explained in more details with an example in appendix 1 of Chapter 2. We checked this procedure with a patent examiner at the EPO office in The Hague in the Netherlands.

Measures at MPA-level

Dependent Variable. The measurement of *MPA innovative performance* in this study context is the aggregated number of granted patents to partner firms within the technological scope of alliances in a 5-year window after the alliance formation, namely *MPA partners' post alliance in-scope patents*. The rationale behind this choice is that in successful R&D partnership, firms tend to legally protect their collective created knowledge in their partnership. We ideally preferred to use patents registered by all partners as joint-assignees; however, the prior studies showed that this practice is not common in high-tech industries due to the legal issues (Hagedoorn, 2003), so we counted the post-alliance registered patents by partner firms as a proxy of their collective created knowledge.

Independent Variables at MPA level. MPA diversity is a multidimensional construct that includes the variety, the separation, and the disparity dimensions. To this extent, we followed Harrison and Klein (2007) guidelines and measured each dimension with respect to their distinct attributes.

For the partner variety, we measured the variation of partner firms' prior-alliance knowledge with respect to different knowledge categories. We used the Blau Index (Blau, 1977) to measure partner variety: $D = 1 - \sum p_i^2$, where 'D' represents degree of diversity, p represents the proportion belonging to a given category 'i' which was coded based on. The variables range from 0 (a perfectly homogeneous group) to 1 (a perfectly heterogeneous group, with members spread evenly among all categories).

For the relational separation, we followed Heidl et al. (2014) suggestion to compute tie strength dispersion. Therefore, to assess tie strength dispersion within each multi-partner alliance k in year t-1, we counted the number of prior ties formed by each dyad in the multi-partner alliance in a five-year moving window (i.e., t-5 to t-1). The strength of each prior tie was weighted based on the scope of activities that occurred in the prior alliance: 2 if technology co-development is involved and 1 for other activities. We then computed tie strength variance across multiple dyads within each sample multi-partner alliance for each year. Variance is essentially a measure of polarization that suits measuring of this variable (Harrison & Klein, 2007). A value of 0 indicates that tie strength is equal across all partner pairs. Higher values of variance indicate that tie strength within a multi-partner alliance is concentrated among a subset of partner pairs.

For the status disparity, we used Bonacich centrality, to measure a firm's positional embeddedness. That is, we measured the Bonacich centrality for all sample firms based on their collaborative activities in the global alliance network. Then, we followed Harrison and Klein (2007) to calculate the coefficient of variation (i.e., Standard Deviation (SD)/mean) of positional embeddedness among the multi-partner alliance members. Aligned with our definition for this dimension, the coefficient of variation captures the relative dominance in the MPA of partner firms with high levels of global network centrality.

Control Variables. We included several additional control variables to exclude alternative explanations. First, the innovative performance of partner firms before the alliance formation may partially address the innovative performance of partner firms after the alliance formation. We used the number of registered patents within the alliance scope by partner firms before the alliance formation, MPA partners' pre-alliance in-scope patents, *as MPA partners' pre-alliance innovative performance*. Moreover, we control for *MPA partners' pre-alliance patents*. This variable can also help control for the aggregated size of partner firms, as it addresses the size of financial and non-financial resources that come with firm size (Sampson, 2007).

Second, there are some other features of the partner firms that might be related to the independent variables described above and that may affect the observed innovative performance of MPA. To this end, we control for several variables with respect to all dimensions of diversity. We control for the partner variety regarding the SIC code (Ozcan & Overby, 2008). We measured it by calculating the Blau index of 4-digit SIC codes as *Partner SIC variety*. We also defined *Partner government mode variety dummy* to address whether all the partner firms are either public or private (=0), or a mixed of these two types (=1). In addition, we considered the average of the weighted prior alliance numbers, *Within MPA mean of prior alliances*, to distinct between the relational separation in an MPA with high number of prior alliances and an MPA with lower number of prior alliances. In the same vein, we controlled for *Within MPA mean of centrality* to distinct between the status disparities between MPAs with high status firms and those with low status firms.

Finally, we defined dummy variables to control for Joint Ventures (*JV*) and *Cross border alliance dummy*, as prior suggested that JVs can provide a better platform for learning (Mowery et al, 1996) and international alliances may demonstrate different dynamics of R&D collaborations (Lane, Salk, and Lyles, 2001). We also control for the *Number of partner firms* and a year indicator for the study time interval (we divided the time-interval of our sample to three 6-year period).

Measures at firm-level

Dependent Variable. To measure value appropriation, we measure the firm's proportional innovative performance. That is the number of post-alliance patents, granted within the technological scope of alliance, by the firm divided by all post-alliance patents, granted within the technological scope of alliance, by all partner firms, namely *Firm's proportional post alliance in-scope patents*. The rationale behind this choice is that we assumed that this measure reflects their appropriated value, or more precisely the acquired knowledge, from their partnership in compared to their counterparts at the same alliance.

Moderating variables at the firm level. For measuring the firm's *Internal knowledge variety*, we measured the variation of partner firms' prior-alliance knowledge with respect to different knowledge categories. We used the Blau Index (Blau, 1977) to measure partner variety: $D = 1 - \sum p_i^2$ where 'D' represents degree of diversity, p represents the proportion belonging to a given category 'i' which was coded based on. The variables range from 0 (a perfectly homogeneous group) to 1 (a perfectly heterogeneous group, with members spread evenly among all categories).

For measuring the broker status of partner firms within MPA, we used the ratio of the mean to the standard deviation of the number of prior alliances of each partner firm. With this approach, partner firms with high and equal numbers of prior alliances with their counterparts get the higher values, consistent with the situation of brokerage role in MPAs.

Finally, for measuring the status of partner firms we used the Bonacich centrality of each partner firm, as the common measure for the status of the firms (e.g., Shipilov & Li, 2008).

Control Variables. We included several additional control variables both at firm-level and MPA-level to exclude alternative explanations. At the firm level, we controlled for the *Firm's proportional pre-alliance in-scope patents, Firm's pre-alliance total patents*, *Firm's pre-alliance in-scope patents*, and *SIC codes*.

At MPA level, we controlled for *Partner SIC variety, Partner government mode variety dummy, Within MPA mean of prior alliances, Within MPA mean of centrality, Joint venture dummy,* and *Number of partner firms*, as it explained above.

Statistical Methods

In this study, we deal with two levels of analysis, MPA and firm levels. At MPA level, the dependent variable of our model is a count variable that has high variance relative to its mean, over-dispersed, so we used negative binomial regression analysis. The likelihood-ratio (LR) test of dispersion parameter (i.e., α) shows α is significantly greater than zero in all our models, so confirming over dispersion in data and supporting our choice of negative binomial over poisson.

At the firm level, each partner firm is nested in a multi-partner alliance, and both MPA and firm level variables are taken into account in the analysis, suggesting the choice of a multilevel model to test the hypotheses. Moreover, the dependent variable is fraction, varies between 0 and 1. Thus, we initially run a generalized linear mixed model (GLMM). However, the higher level of variance appeared trivial, and the log likelihood test to compare GLMM and GLM model (i.e., single level model) was not significant. Therefore, we picked a fractional response regression with logit model (fractional logit model) (Papke & Wooldridge, 1996) that fit the dependent variable. We chose fractional logit model over the beta regression as the dependent variable includes multiple zeros not allowed in beta regression.

RESULTS

Results at MPA level

Table 1 presents the descriptive statistics and correlations at MPA level. The mean of *MPA innovative performance* (2047) as well as *MPA partners' pre-alliance innovative performance* (1265) show that the aggregation of firms' registered patent is significantly increased after the alliance formation ($p<0.001$ in t-test). The correlation among predictor variables are not critically high. We performed a diagnostic test using the "collin" procedure in STATA to check for multicollinearity issue. The test showed no VIF higher than 3.2 and the conditioning numbers of the models were all less 20, all less than the suggested threshold for VIF, 10, and conditioning number, 30 (Table 2); this indicates that multicollinearity does not affect our results (Belsley & Kuh, 1993)[11].

Table 2 shows the results of hypothesis tests at MPA level. Model 1 includes only the control variables. The control variables reports can be subject to inaccuracy due to other possible explanations (Cinelli & Hazlett, 2018), so we just mention the most noticeable results with caution. The results show that *MPA partners' pre-alliance innovative performance* is positively associated with innovative performance of MPA. The results show a negative but insignificant association between MPA innovative performance and the variety of partners'

[11] We acknowledge that the collinearity test suits linear regression models, and although our test is common in extant research, the relevancy of the results should be consider with cautious. However, our robustness tests did not show any indication of multicollinearity in our models.

TABLE 1: Descriptive Statistics (MPA LEVEL)

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**MPA innovative performance**	1.00												
2	**Partner Knowledge variety**	-0.03	1.00											
3	**Relational separation**	0.42	0.12	1.00										
4	**Structural disparity**	0.09	0.11	0.36	1.00									
5	**MPA partners' pre alliance innovative performance**	0.88	-0.01	0.48	0.03	1.00								
6	**MPA partner firm pre alliance patents**	0.47	0.10	0.47	0.02	0.68	1.00							
7	**Partner SIC variety**	-0.08	-0.09	-0.09	-0.15	-0.05	-0.08	1.00						
8	**Partner government mode variety dummy**	-0.16	-0.10	-0.23	-0.02	-0.18	-0.29	0.05	1.00					
9	**Within MPA mean of prior alliances**	0.35	0.05	0.67	0.02	0.38	0.55	-0.03	-0.43	1.00				
10	**Within MPA mean of centrality**	0.19	0.06	0.07	-0.01	0.12	0.20	-0.14	-0.09	0.20	1.00			
11	**Joint venture dummy**	-0.01	0.21	0.17	0.09	0.05	0.17	-0.07	0.15	0.05	0.00	1.00		
12	**Cross border alliance dummy**	0.01	-0.04	-0.12	-0.10	0.01	0.09	-0.06	-0.07	0.07	0.08	0.04	1.00	
13	**Number of partner firms**	0.37	0.00	0.16	0.12	0.26	0.18	-0.09	0.24	-0.07	0.06	0.24	-0.09	1.00
	Mean	2047.22	0.60	0.19	0.41	1265.34	7714.28	0.02	0.50	0.22	0.02	0.18	0.14	3.76
	S.D.	2759.07	0.22	0.19	0.23	2041.59	7427.14	0.15	0.50	0.24	0.01	0.38	0.35	1.33
	Min	0.00	0.00	0.00	0.00	0.00	4.00	0.00	0.00	0.00	0.00	0.00	0.00	3.00
	Max	15600.00	0.86	1.00	1.00	17100.00	51000.00	1.00	1.00	1.00	0.07	1.00	1.00	9.00

modes as well as partners' industries. These results are unreliable but consistent with the findings of alliance portfolio studies (Jiang et al., 2010) and suggests that MPAs with different types of partners' government mode and industry are less innovative than uniform MPAs with those respects, due to lower levels of mutual understanding and incentive across partner firms.

In Model 2, the variable Partner variety is introduced to test H1. The results support the hypothesize inverted-U shape relation between Partner variety and MPA innovative performance. Partner variety is positive and significant (Model 2: $\beta = 16.250$, SE = 1.791, $p = 0.000$), and Partner variety squared is negative and significant (Model 2: $\beta = -13.930$, SE = 1.746, $p = 0.000$). We followed Haans et al. (2016) recommendation for testing the curvilinear relations. The slope tests at the lower range is positive and significant ($\beta = 16.254$, SE = 1.791, $p = 0.000$), and at the highest range is negative and significant ($\beta = -7.772$, SE = 1.387, $p = 0.000$). In addition, the turning point at which Partner variety begins to exhibit a negative effect on firm learning occurs at 0.583 ($\beta = 0.583$, SE = 0.213 , $p = 0.000$), within the data range (0, 0.86), and 39.4 percent of observations have *Partner variety* values below that level. All confirms a quadratic relation in which MPA innovative performance increases with partner variety and hits its maximum at the 39th percentile of partner variety range, but after that, the positive association turns to be negative.

In Model 3, we included the variable *Relational separation* to test H2. The results support the hypothesize inverted-U shape relation between *Relational separation* and *MPA innovative performance*. *Relational separation* is positive and significant (Model 3: $\beta = 9.110$, SE = 1.810, $p = 0.000$), and *Relational separation squared* is negative and significant (Model 3: $\beta = -15.130$, SE = 2.595, $p = 0.000$). The slope tests at the lower range is positive and significant ($\beta = 9.110$, SE = 1.810, $p = 0.000$), and at the highest range is negative and significant ($\beta = -10076.89$, SE = 1728.368, $p = 0.000$). In addition, the turning point at which Relational separation begins to exhibit a negative effect on firm learning occurs at 0.301 ($\beta =$

TABLE 2: Negative Binomial Estimates for MPA Diversity and Value Creation

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Partner variety (H1)		16.25***			14.43***
		(1.791)			(1.750)
Partner variety squared (H1)		-13.93***			-12.67***
		(1.746)			(1.716)
Relational separation (H2)			9.110***		7.691***
			(1.810)		(1.954)
Relational separation squared (H2)			-15.13***		-13.27***
			(2.595)		(2.531)
Structural disparity (H3)				0.459	-0.563
				(1.656)	(1.437)
Structural disparity squared (H3)				0.563	0.583
				(1.820)	(1.523)
MPA partners' pre-alliance innovative performance	0.000651***	0.000694***	0.000657***	0.000629***	0.000656***
	(0.000109)	(9.51e-05)	(8.70e-05)	(0.000107)	(7.89e-05)
MPA partner firm pre-alliance patents	3.14e-06	-1.11e-05	2.02e-05	1.82e-05	-1.16e-05
	(2.51e-05)	(2.14e-05)	(2.52e-05)	(2.35e-05)	(2.17e-05)
Partner SIC variety	-1.167	-0.687	-1.516**	-0.873	-1.008
	(0.752)	(0.678)	(0.725)	(0.761)	(0.667)
Partner government mode variety dummy	-0.328	-0.390**	-0.242	-0.444**	-0.310
	(0.233)	(0.196)	(0.224)	(0.222)	(0.195)
Within MPA mean of prior alliances	0.617		0.384		0.184
	(0.645)		(0.701)		(0.655)
Within MPA mean of centrality	14.84			17.30*	16.53**
	(9.815)			(9.930)	(8.065)
Joint venture dummy	0.161	0.0885	0.311	0.152	0.387
	(0.297)	(0.275)	(0.277)	(0.292)	(0.256)
Cross border alliance dummy	-0.0864	0.0211	0.109	0.0338	0.0689
	(0.323)	(0.286)	(0.316)	(0.332)	(0.275)
Number of partner firms	0.0896	0.0402	0.0234	0.0721	0.0331
	(0.0902)	(0.0771)	(0.0865)	(0.0922)	(0.0771)
SIC dummies	included	included	included	included	included
Year dummies	included	included	included	included	included
Constant	4.767***	1.403**	3.968***	4.330***	1.087*
	(0.661)	(0.576)	(0.630)	(0.766)	(0.653)
Observations	137	137	137	137	137
Log Likelihood	-1082	-1060	-1071	-1080	-1047
Degree of Freedom	18	18	19	19	24
Wald's chi square	1.20E+05	1.20E+05	7.70E+03	1.20E+05	6.70E+04
α (dispersion parameter)	1.314	1.016	1.155	1.291	0.856
Condition number |Mean VIF	13.94|2.92	14.20|2.68	14.08|3.14	13.39|2.69	19.21|2.95

Note: Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

0.301, SE = 0.273 , p = 0.000), within the data range (0, 1), and 74.5 percent of observations have Relational separation values below that level. All confirms a quadratic relation in which MPA innovative performance increases with relational separation and hits its maximum at the

75th percentile of relational separation range, but after that, the positive association turns to be negative.

In model 4, we included the variable *Structural disparity* to test H3. The results do not support the hypothesize inverted-U shape relation between *Structural disparity* and *MPA innovative performance*. *Structural disparity* is positive but insignificant (Model 4: β = 0.459, SE = 1.656, p = 0.782), and *Structural disparity squared* is also positive and insignificant (Model 4: β = 0.563, SE = 1.820, p = 0.757). Then we tested the linear relation. The results show a positive but marginal significant between *Structural disparity* and *MPA innovative performance.* The coefficient (β = 0.948, SE = 0.487, p = 0.052) suggests that a one standard deviation increase in *Structural* disparity increase the MPA innovative performance by a considerable factor of 158% ($= e^{0.95} - 1$), while holding all other variables in the model constant.

We next incorporated all the independent variables corresponding to the hypotheses H1, H2, and H3 into Model 5. The results were unchanged. In sum, while the results provide support for H1 and H2, H3 is not supported in our sample.

Results at the firm level

Table 3 presents the descriptive statistics and correlations at the firm level. The correlation among predictor variables are not critically high. We performed a diagnostic test using the "collin" procedure in Stata to check for multicollinearity issue. The test showed no VIF higher than 2.9 and the conditioning numbers of the models were all less 21, all less than the suggested threshold for VIF, 10, and conditioning number, 30 (Table 4); this indicates that multicollinearity does not affect our results (Belsley & Kuh, 1993).

Table 4 shows the estimations results of fractional response regression. Model 1 includes the control variables. The proportion of partner firms' prior alliance in-scope patent number to MPA (total patents) has a significant positive effect on the proportion of partner firms' post alliance in-scope patent number to MPA, as value appropriation (hereafter), and the number of partners has a negative effect; both expectable.

In Model 2, the interaction of internal knowledge variety and partner variety on value appropriation (H4) is tested. The coefficient is positive and significant (Model 2: $\beta = 6.798$, $SE = 1.630$, $p = 0.000$). The marginal plot of interaction terms in Figure 1a shows that when Partner firms' internal knowledge variation increases the marginal effect of partner knowledge variety on partner firm's value appropriation increases, supporting H4.

Model 3 includes the interaction of brokerage-role of the partner firms with relational separation to address the H5. The coefficient is positive and significant (Model 3: $\beta = 0.192$, $SE = 0.0076$, $p = 0.010$). The marginal plot of interaction terms in Figure 1b show that as the broker status increases the positive effect of relational separation on partner firm's value appropriation increases, supporting H5.

Model 4 addresses H6, in which we asserted that partner firms with a higher status take more advantage from the disparity in their partnerships. The coefficient of interaction term is positive and marginally significant (Model 4: $\beta = 23.354$, $SE = 0.383$, $p = 0.053$). The marginal plot of interaction terms in Figure 1c illustrates how with increasing the status disparity of partner firms, firms with stronger network position benefit from status disparity, marginally supporting H6.

Finally, we incorporated all the independent variables corresponding to the Hypotheses H4, H5, and H6 into Models 5, 6, 7 respectively. The results for interaction variables were unchanged in each model. In sum, the results provide support for H1 and H4, and marginally for H6.

TABLE 3: Descriptive Statistics (Firm Level)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Firm's proportional post alliance in-scope patents**	1.00															
2	**Internal knowledge variety**	0.15	1.00														
3	**Broker status**	0.19	0.13	1.00													
4	**Bonacich Centrality**	0.22	0.27	0.22	1.00												
5	**Partner variety**	-0.42	0.16	0.00	0.03	1.00											
6	**Relational separation**	-0.14	0.04	0.00	0.02	0.11	1.00										
7	**Structural disparity**	-0.11	-0.07	0.01	-0.04	0.06	0.39	1.00									
8	**Firm's proportional pre-alliance in-scope patents**	0.88	0.16	0.16	0.23	-0.41	-0.14	-0.10	1.00								
9	**Firm's prior alliance total patents**	0.27	0.42	0.22	0.34	0.06	0.26	-0.02	0.28	1.00							
10	**Firm's prior alliance in-scope patents**	0.21	0.24	0.07	0.24	-0.05	0.34	0.02	0.23	0.57	1.00						
11	**Partner SIC variety**	0.02	-0.05	-0.01	-0.09	-0.08	-0.09	-0.14	0.01	-0.03	-0.03	1.00					
12	**Partner government mode variety dummy**	0.07	-0.23	-0.09	-0.04	-0.07	-0.17	0.03	0.07	-0.25	-0.18	0.03	1.00				
13	**Within MPA mean of prior alliances**	-0.09	0.18	0.15	0.10	0.06	0.69	0.05	-0.09	0.39	0.32	-0.03	-0.40	1.00			
14	**Within MPA mean of centrality**	-0.04	0.09	0.04	0.65	0.05	0.03	-0.05	0.00	0.12	0.06	-0.13	-0.07	0.16	1.00		
15	**Joint venture dummy**	-0.09	0.04	0.00	0.01	0.24	0.21	0.07	-0.09	0.05	-0.03	-0.07	0.13	0.07	0.01	1.00	
16	**Number of alliance partners**	-0.16	-0.06	-0.12	0.05	-0.02	0.22	0.19	-0.14	-0.09	0.02	-0.10	0.24	-0.07	0.07	0.26	1.00
	Mean	0.22	0.73	5.77	0.02	0.60	0.20	0.42	0.20	2071.77	204.11	0.02	0.55	0.21	0.02	0.21	4.22
	S.D.	0.28	0.34	17.33	0.02	0.22	0.20	0.24	0.26	3098.48	435.88	0.13	0.50	0.23	0.01	0.41	1.70
	Min	0.00	0.00	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.00
	Max	1.00	0.99	266.58	0.14	0.86	1.00	1.00	1.00	21100.00	3202.00	1.00	1.00	1.00	0.07	1.00	9.00

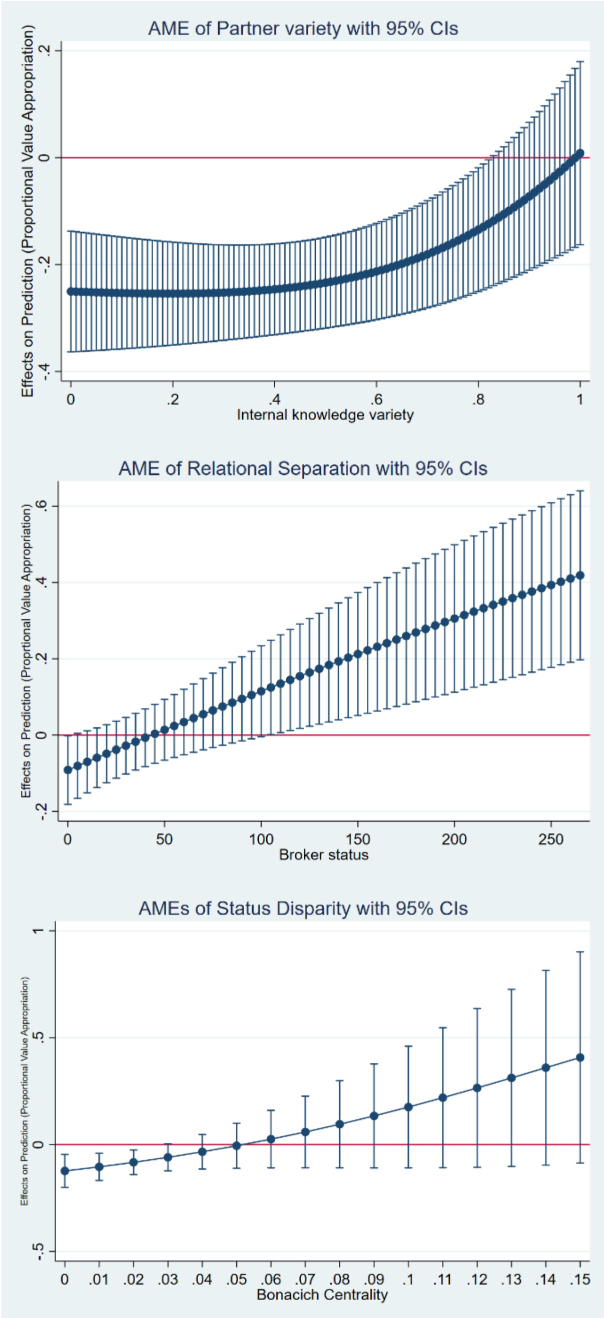
TABLE 4: Fractional Logit Model: Value Appropriation (proportional) at the Firm Level

Proportional value appropriation (Firm's proportional post alliance in-scope patents) (DV)

VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Internal knowledge variety		-1.735*			-1.591*	0.808**	0.840**
		(0.939)			(0.877)	(0.357)	(0.356)
Partner variety		-6.733***			-6.213***	-1.350***	-1.332***
		(1.418)			(1.270)	(0.493)	(0.493)
Internal knowledge variety*Partner variety		6.798***			6.210***		
		(1.630)			(1.485)		
Broker status			-0.00524		7.73e-05	-0.00458	-0.000884
			(0.00362)		(0.00154)	(0.00308)	(0.00147)
Relational separation			-0.833**		-0.0226	-0.119	-0.0132
			(0.409)		(0.397)	(0.435)	(0.384)
Broker status*Relational separation			0.0192**			0.0132*	
			(0.00751)			(0.00718)	
Bonacich centrality				1.577	13.47***	14.99***	0.594
				(7.270)	(3.285)	(3.691)	(7.592)
Structural disparity				-1.220***	-0.549**	-0.797***	-1.200***
				(0.371)	(0.270)	(0.291)	(0.402)
Bonacich centrality*Structural disparity				23.54*			24.76**
				(12.15)			(12.36)
Firm's proportional pre-alliance in-scope patents	5.401***	4.731***	5.373***	5.199***	4.529***	4.911***	4.871***
	(0.394)	(0.403)	(0.395)	(0.383)	(0.427)	(0.418)	(0.420)
Firm's pre-alliance total patents	4.89e-05***	1.71e-05	4.93e-05***	3.79e-05**	1.66e-05	3.61e-05**	3.70e-05**
	(1.81e-05)	(1.77e-05)	(1.79e-05)	(1.63e-05)	(1.70e-05)	(1.75e-05)	(1.77e-05)
Firm's pre-alliance in-scope patents	3.86e-05	0.000105	7.05e-05	1.90e-05	9.24e-05	-3.20e-05	-2.18e-05
	(9.57e-05)	(0.000103)	(9.96e-05)	(9.42e-05)	(0.000105)	(0.000102)	(0.000102)
Partner SIC variety	0.0364	-0.246			-0.410	-0.127	-0.163
	(0.315)	(0.511)			(0.548)	(0.410)	(0.417)
Partner government mode variety dummy	0.0912	0.168			0.132	0.116	0.148
	(0.136)	(0.124)			(0.124)	(0.132)	(0.128)
Within MPA mean of prior alliances	-0.0247		0.110		0.00547	-0.0708	-0.102
	(0.287)		(0.334)		(0.368)	(0.367)	(0.357)
Within MPA mean of centrality	-8.120*			-20.14***	-25.12***	-24.33***	-18.28***
	(4.932)			(6.856)	(5.914)	(6.571)	(6.772)
Joint venture dummy	-0.119	-0.0934	-0.0785	-0.121	-0.111	-0.00244	-0.0170
	(0.132)	(0.129)	(0.123)	(0.120)	(0.127)	(0.122)	(0.121)
Number of partner firms	-0.121**	-0.141***	-0.0936*	-0.110**	-0.136***	-0.125**	-0.131**
	(0.0536)	(0.0460)	(0.0479)	(0.0444)	(0.0473)	(0.0513)	(0.0512)
Firm SIC dummies	included	included	included	included	included	included	included
Year dummies	included	included	included	included	included	included	included
Constant	-2.097***	-0.00968	-2.097***	-1.439**	0.328	-1.331*	-1.221
	(0.523)	(0.853)	(0.536)	(0.581)	(0.817)	(0.788)	(0.796)
Observations	509	509	509	509	509	509	509
Log Likelihood	-183.3	-178.1	-183.2	-181.6	-176.9	-179.8	-179.7
Pseudo R squared	0.31	0.329	0.311	0.316	0.334	0.323	0.324
Condition number |Mean VIF	10.25|1.93	15.00|1.97	10.04|2.27	10.69|2.16	20.73|2.9	20.73|2.10	20.73|2.11

Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

FIGURE 1a, b, & c:
The marginal effect plot of interaction terms for Firm's internal knowledge variety and Partner variety in MPAs (a: the upper one), for Firm's broker status and Relational separation in MPAs (b: the middle one), and for the Firm's Bonacich centrality and structural disparity in MPAs (c: the lowest one).



DISCUSSION

In this study, we investigated the performance consequence of multi-partner alliance diversity at both multi-partner alliance (MPA) and firm levels in the context of research collaboration. We made a distinction among the different types of resources, to underline the distinct dynamics of different dimensions of diversity in multi-partner alliances. Then, we examined the performance variation of both MPA and partner firms with respect to the MPA diversity along each of these dimensions. Our results show while diversity in within-firm resources, namely partner variety, and between-firm resources, namely relational separation, have an inverted U-shaped effect on MPA performance, diversity in network resources, namely status disparity, has a linear positive effect on performance. Our findings also reveal the diverging mechanisms between value creation at the multi-partner alliance level and value appropriation at the firm level regarding each dimension of MPA diversity. We demonstrate that some partners can benefit more than others do, even if the total partnership is worse off, and vice versa. This divergence depends on the advantage or disadvantage of a partner firm to its counterpart in each dimension.

Our systematic approach to examine the performance consequence of MPA diversity contribute to the growing research on multi-partner alliances. Prior research on MPA has shown that how the variation of different types of resources affect the stability and performance of MPAs (Heidl et al., 2014; Xu et al., 2014; X. Yin et al., 2012). We contribute to this stream of research by examining the effect of variation of different types of resources on the collective advantage of partner firms at MPA level as well as the advantage of partner firms in their multi-lateral partnership.

At the MPA level, our results show the performance consequences of variation in different types of resources across partner firms. These findings addressed the quest for research on MPA as a strategic entity (Gomes-Casseres, 2003; Lavie et al., 2007). With this respect, this study bridges between research on MPAs and the longstanding stream of strategy research on the performance consequence of diversification strategy (Rumelt, 1982; Montgomery, 1985; Markides & Williamson, 1996; Richter et al., 2017; Ahuja & Novelli, 2017). In the context of multi-partner alliances, as collective, voluntary organizational associations, diversification is a consequence of the initial decision of partner firms at the time of alliance formation, as well as the decision of partner firms to stay, leave, or invite and accept the new partners to join their alliance. Our findings show that diversity in different types of resources leads to distinct rent variation at both MPA and firm levels. This approach addresses the call in the literature for more fine-grained theoretical and empirical analysis of the mechanisms through which diversity adds or subtracts value (Ahuja & Novelli, 2017).

At the firm level, our findings show how a partner firm's resource attributes condition the value that it appropriates from their partnerships. Only a few studies in IOR research have elaborated on the moderating role of firm's resource attributes in the appropriation of total created value in its partnerships. For example, in alliance portfolio research, Srivastava and Gnyawali (2011) showed that how the technological diversity and strength of a focal firm condition the positive impact of diversity and quality of resources in the alliance portfolio on the rate of breakthrough innovation. We contribute to this approach and examine how MPA diversity in each dimension moderates the relation between firm's resource attributes and its value appropriation.

Our findings also contribute to the understanding of value creation and appropriation mechanisms of MPAs by taking into account both the value creation at the MPA and the value appropriation mechanisms at the firm levels in the same study. On one hand, the value creation mechanism at the MPA is a function of partner firms' contributed resources to MPA as well as the dynamics of cooperation and coordination of partner firms in their mutual effort (Gulati et al., 2012; Gulati, 1998). On the other hand, the value appropriation mechanism at the firm level depends on the value of firms' contributions, as well as their internal resources, their brokerage position, and their status and power (Adegbesan & Higgins, 2011; Dyer et al., 2008; Lavie, 2006; Lavie et al., 2007). Our findings show the divergence of these two mechanisms at MPA and firm levels in such a way that the value creation mechanisms in MPAs may not be compatible with the value appropriation mechanism in partner firms. In simple words, we show that what is beneficial for the alliance is not necessarily beneficial for all partner firms, and vice versa.

Moreover, this study offers some managerial implications. The diverging mechanisms of value creation and appropriation in MPAs suggests that managers should pay attention to the trade-off between MPA performance and the proportional performance of partner firms in their decision to join, stay, or leave an MPA. The proportional performance of partner firm is critical at it usually shapes the perceived value of firms and influence their contribution to MPA (Fonti et al., 2017). For example, an SME may not proportionally benefit from staying in a partnership with an optimum diversity due to its resource disadvantages, and consequently decide to leave or reduce their collaboration level, while its absolute performance is higher than joining a partnership with less diversity. As another example, while an MPA has been already divided into subgroups due to its excessive relational separation, a firm with good relations with the MPA subgroup members may still decide to join at the cost of the other members' performance.

Naturally, this research has important limitations. First, the alliances examined in this study are those pertaining to research collaborations, and although our argumentation is general and can apply to all types of alliances, caution is needed regarding the generalizability of our findings to the other types of alliances (e.g., marketing, manufacturing, and supply chain).

Second, our selected measures for the MPA and partner firm's performance are not the most precise measure of the performance, given the accuracy of patents in measuring the firm's (innovative) performance. However, our treatment in specifying the scope of the alliance offers a solution to use patent data in a more precise way to measure innovative performance of the firms. Third, performance is a multifaceted construct and measuring the performance in one aspect may not represent the full realized performance of alliances and partner firms. However, we tried to partially address this issue by narrowing our sample selection strategy to the research collaborations that explicitly specified their research agenda. In addition, the same argument might be applicable to the other aspects of performance such as status accumulation, market share, or financial outcome.

Further studies are needed to understand better the complexity of configurations and dynamics of value creation and appropriation in MPAs. MPAs appear in different forms and we only focus on one form (i.e., R&D collaboration) in this research. Investigating the configuration and dynamics of the other forms of MPAs may improve our general understanding of this phenomenon. Future research might also take into account the other types of performance to further improve our theoretical and empirical understanding of dynamic of value creation and creation in MPAs. This research tried to address the performance of MPAs in a specific context with elaboration on the alliance scope. However, we believe that it is necessary to have a systematic examination of alliance performance measures at the alliance level, rather than the common focal firm level. Finally, our approach to systematically examine the diversity in the context of multi-partner alliances can apply to other relevant phenomena such as alliance portfolios and corporate firms.

CHAPTER 4

INCUMBENT SUCCESS IN THE ERA OF FERMENT: NAVIGATION OF INTERGENERATIONAL TRANSITION OF LITHOGRAPHY TECHNOLOGY WITHIN ASML

ABSTRACT

How can some incumbent firms proactively navigate technological change while others fail to do so? We explore this question by studying the dynamics of incumbents' engagement in an era of ferment, in which new technological options challenge the dominance of the current technology generation. We take a real option theory perspective and focus on a successful incumbent firm, ASML, in a period when varieties of new technological options were threatening the dominance of the optical-lithography regime. Our findings show that ASML managed this turbulent period in such a way that it gained the core position in both the existing and in the new technological regime. First, ASML proactively engaged in the experimental development of technological options. Second, ASML persistently relied on the scientific rules of physics and economics, rather than on their current performance, in the assessment of the long-term feasibility and extendibility of technological options. Third, timely commitment to and abandonment of technological options in its portfolio enabled ASML to play an active role in the dynamics of transition to the next generation of lithography technology.

Keywords: *the era of ferment; decision-making under uncertainty; real option*

INTRODUCTION

Technological change starts with a turbulent period, the so-called era of ferment, in which new, emerging technologies challenge the dominance of existing technologies (Anderson & Tushman, 1990). In this era, there is an intense competition between technologies, as well as between new and existing technologies, to dominate the market (Anderson & Tushman, 1990; Dosi, 1982). During this period incumbents need to take timely actions to survive, but their established core and complementary capabilities, which give them the edge in the reign of existing technology, may be a liability at this time (Tushman & Anderson, 1986).

Research has extensively studied the competition between old and new technologies (e.g., Anderson & Tushman, 1990; Dosi, 1982), the success factors of winner technologies (e.g., Schilling, 1998, 2002), and the strategic actions of incumbent and new firms in the era of ferment (e.g., Tripsas, 1997). However, it has mainly focused on the reaction of incumbent firms to the rise of new technologies, rather than their possible proactive engagement in the development and selection of these technologies. Therefore, the proactive engagement of incumbents in the era of ferment has remained largely unstudied, with only a few exceptions (Eggers, 2016; Eggers & Kaul, 2017; Moeen & Agarwal, 2016). A potential reason for this oversight is that this research stream mainly considers the emergence of a new technology as an exogenous shock, which punctuates the existing technology trajectory, and examines the heterogeneity of incumbents' responses (for a recent review see Eggers and Park (2018)). In addition, these studies mainly apply theoretical lenses such as resource-based view, dynamic capabilities, or ambidexterity to examine the heterogeneity of incumbent firms' reaction to technological changes. However, while these theoretical lenses describe how companies explore and adopt to these new technologies in general, they do not offer the required framework to understand the incumbents' behaviors in the era of ferment (Chi et al., 2019; Raisch & Tushman, 2016). How do they choose between different emerging technologies, and how do they decide to scale up, or to end their inquiries? Moreover, how may their behavior affect the selection process of a new dominant technology?

In this study, we explore the proactive engagement of incumbents in the development of different technological options and their potential influence in the selection of the next dominant technology. We qualify the punctuated-equilibrium based explanation of the era of ferment, by incorporating a gradual model of technology growth. This approach enables us to trace the proactive engagement of incumbent firms in the era of ferment.

We conducted an explorative case study to understand the dynamics of the era of ferment and the rationale of a successful incumbent's behavior. We chose an exemplary incumbent firm, ASML, which successfully passed through a turbulent period in the lithography equipment industry, in which a variation of existing optical-lithography technologies and emerging particle-based and X-ray technologies competed to become the next dominant technology. To understand ASML's actions in this uncertain period, we apply a real option perspective. The real option view equips us with a dynamic, forward-looking perspective to study how ASML identified, invested in, abandoned, or continued technological options.

Our findings offer several contributions to research in technological change as well as to real option theory. Our detailed observations shed light on the evolutionary side of technological discontinuity. We revisit the punctuated-equilibrium based explanation of the era of ferment and delineate the technology selection process in this era. Our findings reveal how ASML managed the era of ferment in such a way that it gained the core position in both the existing and the new technological regime. First, ASML proactively engaged in the experimental development of technological options. Second, ASML persistently relied on the scientific rules of physics and economics in the assessment of the long-term feasibility and extendibility of technological options, rather than on the current state of their performance. Finally, the timely commitment to and abandonment of technological options, alongside the formation and termination of corresponding collaborations that ASML engaged in, enabled ASML to play an active role in the transition of the industry to the next generation of lithography technology. Our study not only answers to the recent call for detailed examination of real option portfolios consisting of interdependent options (Trigeorgis & Reuer, 2017), it also offers a unique insight into the dynamics of endogenous and exogenous uncertainties over the course of technological change, within a portfolio of technological options.

BACKGROUND: ENGAGEMENT IN THE ERA OF FERMENT

The Battle of Technologies in the Era of Ferment & the Proactive Engagement of Incumbent Firms

The process of technological change as well as the heterogeneity of incumbents in adapting to new technology has been a center of attention in the strategy literature. At the technology level, earlier research has focused on the modeling of this transition by either continuous models, such as the S-form model (Adner & Kapoor, 2016; Foster, 1988; Sood et al., 2012), or by discontinuous models such as the cyclical punctuated equilibrium model, to highlight the discontinuity between the existing dominant technology and new technologies (Anderson & Tushman, 1990). Both perspectives highlight the dynamics and the uncertainty of this transition in the so-called era of ferment, in which a variety of new and existing technologies compete to become the next dominant technology (Anderson & Tushman, 1990). At the firm level, studies have mainly developed discontinuous models of technological change and focused on the antecedents of incumbents' heterogeneous responses to technology change (see Eggers and Park (2018) for a recent review).

These studies offer significant insights into the patterns of technology change, and the heterogeneity of incumbents' adaptation to this change. However, there are some interrelated shortcomings in both groups of studies. First, at the technology level, studies fall short to offer an integrative view that covers both continuous and discontinuous change (for an exception see Adner & Kapoor, 2016). Therefore, we know less about the issue of timing in the era of ferment; when emergent technologies start challenging the existing one, and when the winner technology comes out of the selection process and starts its domination. At the firm level, studies take new technologies as exogenous shocks that provoke reactions from incumbents to survive. Therefore, their possible proactive engagement in the era of ferment is largely ignored (for an exception see Eggers (2016)).

We believe that this deficiency is mainly rooted in the fact that firm-level studies conceptualize technological change mainly based on the discontinuous model, and overlook the gradual and continuous development of disruptive technologies over time. Therefore, they focus on the period when a new superior technology has already been developed to the level that it can seriously challenge and discontinue the existing technology. In this approach, there is no room for considering the early engagement of incumbent firms in the development and selection of new technologies, as well as the competitive dynamics between varieties of new and existing technologies.

However, there are several examples of new technologies that failed to replace the existing technology, such as bubble memory that failed to challenge random access memory (Cockburn, 2003). Also, some incumbent firms not only passed through several technological changes in their history, but also took the lead in many of these changes. For example, Intel Company has been an industry leader for decades and has continuously discontinued technologies in its successive microprocessor generations. The current study explores how incumbent firms can be successful across technology generations, by focusing on their proactive engagement in technology development and decision making in the era of ferment.

Real Option Perspective to the Management of Technological Choice in the Era of ferment

We started our inductive exploration of the challenges of proactive engagement of incumbents during the era of ferment on the basis of an interest in this phenomenon, rather than to develop or apply a specific theoretical perspective. However, we soon realized that the real option perspective could guide our inquiry and help us frame our research questions and findings. The real option perspective is a proper choice to examine irreversible decision-making processes under uncertainty, when the option value is not known ex ante, and the future opportunities are a function of prior investment commitments (Bowman & Hurry, 1993; McGrath, 1997; Trigeorgis & Reuer, 2017; Chi et al., 2019). The real option view is particularly applicable when investments are divisible and sequential, and when having the possibility of deferring the decision to expand or abandon the investment can increase the chance of the upside outcome while reducing downside risk of decision making under uncertainty (Adner & Levinthal, 2004; Klingebiel & Adner, 2015; McGrath et al., 2004).

Received research into technological change has mainly relied on arguments based on resource-based theory (Tushman & Anderson, 1986), the dynamic capabilities perspective (Danneels, 2011), or the ambidexterity view (Taylor & Helfat, 2009) in examining survival antecedents of incumbents in the face of technological change. These perspectives mainly assume that incumbents react to technological discontinuities, and offer limited insight into incumbents' proactive engagement in the era of ferment (Chi et al., 2019; Raisch & Tushman, 2016). In contrast, a real option perspective offers a dynamic and forward-looking framework to examine the firm's proactive decision-making and actions in this turbulent period, in which the outcome of competition among technological option is not clear ex ante, but the incumbents' success is a function of their timely commitment to the winning option (Eggers, 2016; McGrath et al., 2004).

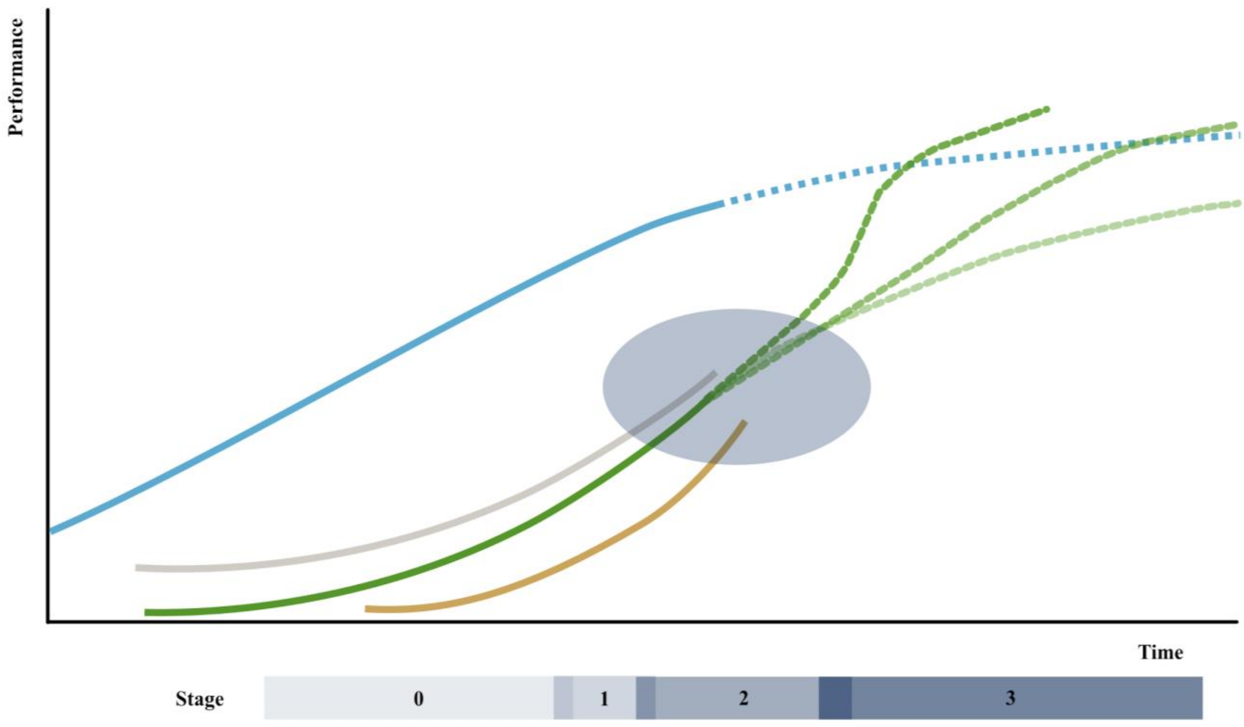
We believe that not only real option theory is a proper perspective to examine incumbents' behavior in the era of ferment; the era of ferment also is a unique context to expand the application of real option theory in strategy research. First, the dynamics of the era of ferment fit the real option life cycle. On one hand, the era of ferment starts with the emergence of new technologies that challenge the continuity of existing technology dominance, then competition follows over performance and compatibility with the supporting ecosystem between developing new technologies and extended existing technology, and finally this turbulent period ends with the domination of the winner technology. On the other hand, the life cycle of real options starts with the identification of hidden options, creation or acquisition of an option at a premium, preservation and management of the firm's real option portfolio, and finally valuing and exercising the selected one(s) and abandoning the others (Trigeorgis & Reuer, 2017, p. 47; Bowman & Hurry, 1993). Therefore, examination of incumbent firms with respect to technological options over the different stages of the era of ferment fits our firm-level analysis of the dynamics of technological competition at the technology level. We specifically examine how the timing and management of the technological options in the era of ferment can determine the success of incumbents.

Second, the era of ferment is marked by multi-lateral competition between a variety of emerging technologies and the existing technology, so incumbent firms may identify and create a bundle of competitive technological options among all the possible choices to minimize their downside risk and maximize their benefit (Vassolo et al., 2004). The technological portfolio in the era of ferment is a particular case. There are just a few competitive options available in this period to be chosen by few actors, so adding one option influences the underlying socio-technological mechanisms that determine the value and uncertainty of other options. Therefore, examination of incumbents' actions in the era of ferment contributes to our understanding of the dynamics of timing, valuation, and uncertainty of a portfolio of competitive options with limited number, and to a longstanding conversation in the literature on the boundary conditions of real option perspective.

To this end, we articulate our research question based on the real option framework as follows: How do incumbent firms proactively identify, create, and manage a portfolio of competing technological options, and play an active role in the valuation and selection of upcoming technologies during the era of ferment?

The remainder of this study is as follows. After introducing our methods and the context of our study in the next sections, we identify the stages of the era of ferment, and take the perspective of the life cycle of real options to explain ASML's actions in each step (Figure 1).

FIGURE 1: The different stages of technology development in the era of ferment and the lifecycle of real options



	Stage 0	Stage 1	Stage 2	Stage 3
Option Stages	Option identification	Option acquisition	Option Management	Option Exercise
Actions	Discovery of different (hidden) technology options	Create a portfolio of different technology potions	Manage development and selection of technology options	Exercise the selected technology option(s)
Era of Ferment Stages	Perceived fading of the dominance of existing technologies	Selection of different potential challenging technologies	Selecting the most promising next dominant design	The emergence of the new dominant design

Finally, we discuss our findings and formulate our contributions.

METHODS

Research Methods and Context

Given the limited theory and empirical evidence on our research question, we conducted an inductive study of a single case. The inductive approach suits process-based research questions extant studies have not yet thoroughly addressed (Glaser & Strauss, 1971), and a single case study provides the rich and detailed data for our multifaceted research question (R. K. Yin, 2017). We started our study based on the principles of grounded theory (Glaser & Strauss, 1971) to explore our original question on the proactive engagement of successful incumbent firms in technology development and decision making in the era of ferment. Then, we followed an iterative process of moving back and forth between literature and data to take a proper theoretical lens to frame our findings.

We chose an incumbent firm in the semiconductor lithography equipment industry, ASML, that successfully passed the era of ferment. Lithography is a key process used by semiconductor manufacturers to create integrated circuits (ICs) chips. This context attracted many studies as it has experienced several generations of technologies in its explosive growth path over the past half-century (Adner & Kapoor, 2010, 2016; Henderson & Clark, 1990; Iansiti, 2000). We focus on an under-explored period in which different technological regimes such as particle based (i.e., Ion-beam, and E-Beam), and X-ray (i.e., soft X-ray (EUV), and hard X-ray) were competing to be selected as the next generation of lithography technology, called "NGL" in this industry. During this period, which approximately covers the period between the mid-1990s to the mid-2000, emerging technological regimes challenged the domination of existing optical-lithography technology. The domination of each of these technological regimes could come with significant changes in the core technology and ecosystem of the industry. Therefore, the situation corresponds to the conditions of the era of ferment.

We choose ASML as an exemplary successful case. ASML actively engaged in this critical period of the industry in the development of emerging technological regimes, while they also made a significant contribution to the extension of the optical-lithography regime. The result was that ASML came out of this turbulent period as the market leader for both the old and new technological regimes.

Empirical Data and Analytical Method

Data. Our case study proceeded in three stages: first, to understand the technological roadmap of the lithography industry and identify the era of ferment, we conducted a historical analysis of the industry, mainly based on industry reports, industry history, and technical monographs (e.g., Bakshi, 2009; Brown & Linden, 2011), electrical engineering and semiconductor journals (e.g., Harriott, 2001; Ito & Okazaki, 2000), and management studies that used this industry as their research context (e.g., Adner & Kapoor, 2010, 2016; Henderson & Clark, 1990). We also used public data such as financial and patent data, and checked our insights in expert interviews.

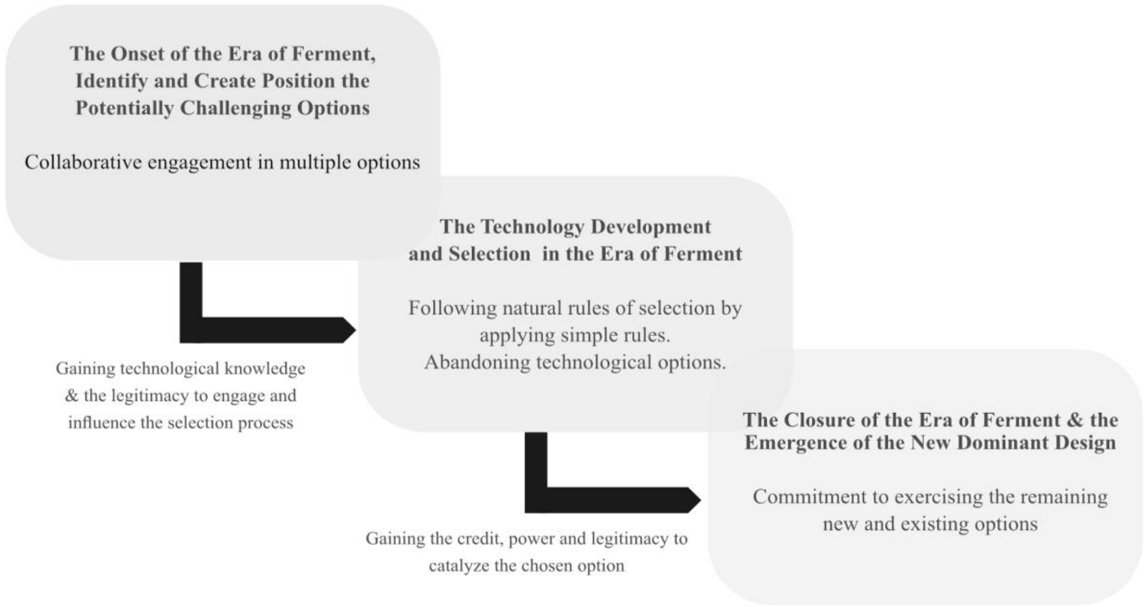
In the second step, we conducted in-depth interviews which formed our main source of information for the study. We followed a snowballing sampling strategy. We started interviewing some of the core decision makers of the period at ASML, to investigate perceptions of the situation, decisions, and rationales behind decisions. Then we asked them to provide us with the list of people who were engaged in decision making within ASML and across the industry. One of our key respondents in ASML provided us with lists of industry experts who participated in and contributed to SEMATECH conferences, a consortium in charge of navigation of semiconductor technology roadmaps. We used this comprehensive list of top experts and decision makers in each interview and asked the respondent whether they could introduce us to one of these experts or add a new name to this list. As the result, we interviewed some of the most influential players in the ecosystem to triangulate our findings from the ASML interviews. In total, we have conducted twenty semi-structured interviews with twelve senior people from major players in this industry at that period, such as ASML, Intel, AMD, IMS, IMEC, Zeiss, and SEMATECH. Respondents also shared useful documents with us, such as product roadmaps, technology papers to which they contributed, and SEMATECH documentation. Some of the respondents provided us also with the videos or transcriptions of interviews they had given in the past. All interviews were in-depth interviews of about 60 to 120 minutes with specific sets of questions concerning the interviewee's area of expertise and affiliation during our target period. We checked these findings with archival documents and conducted follow-up interviews in order to clarify additional questions raised after comparing participants' answers.

All the interviews were recorded, transcribed verbatim, and sent back to the respondent for confirmation. Then, we used ATLAS software to store and classify the data sources and to perform the code systematically.

Analytical Method. Given the limited number of interviews, and the fact that these were specifically targeting the research questions, we decided that it was not necessary to employ a coding method (see Gläser & Laudel, 2013). Our analysis was focused on the stages in the process of technological change, forms of commitment to technological options, ASML's decision processes, technology selection mechanisms at industry level, and timing of exercise or abandonment of technological options.

Moreover, we built a comprehensive timeline of the major events and ASML's actions during the era of ferment. Our analysis revealed three different stages in the development of the era of ferment. These three stages are represented in Figure 2.

FIGURE 2: Three stages in the era of ferment



THE ERA OF FERMENT IN SEMICONDUCTOR LITHOGRAPHIC EQUIPMENT INDUSTRY

The Fundamental Drivers of Continuous Advancement in Lithography Technology

Lithography equipment is at the heart of the chip manufacturing process. In the long and complex process of chip production, imprinting the designed chip on silicon wafers via lithography equipment is the most challenging and expensive step. The most added value and competitive advantage lies at this stage; hence, investing in this step of the process is crucial. From the early stage of the semiconductor industry, two industry-wide accepted laws have navigated the technological advancement of lithography equipment: Moore's law on the demand side and Rock's law on the supply side.

Gordon Moore, the former CEO of Intel, proposed Moore's law in 1965. He predicted that the number of transistors on a microchip should be roughly doubled every other year. Soon, this prediction became a roadmap for industry leaders in order to address the exploding demand of the market in information era and to keep their competitive advantage. In addition, this law has since 1975 been expanded to include the costs per element on a wafer, as production of smaller microchips comes with improvement of the throughput and reduction in cost of raw materials. To serve this demand, Lithography technology as a major bottleneck has been introducing to the market a new technology node – a complete set of working lithography tools and auxiliary components - roughly every 3 years from the '70's to the mid-90. As a result, the industry not only successfully followed Moore's law regarding the feature size of microchips, but also the total cost of production was reduced by 21% per year.

However, this exponential growth comes at a price, as the R&D, the manufacturing, and the testing costs increase steadily with each new generation of technology. This underlying trend on to the supply side is called Rock's law (Ross, 2003), which states that the capital cost of a semiconductor plant doubles every four years. Hence, the investments and risk of developing capital goods and manufacturing line equipment considerably increases as the technology progresses.

While Moore's law pushes the industry forward, Rock's law constrains the choice of industry for new technologies, so the right choice of a new technological solution becomes increasingly difficult and crucial for the industry at each step forward. Industry experts mention that the main enemy of progress is the development cost of a new technological generation, so the extendibility of technology to insure a long-term profitability of incremental progress is more crucial than initial technical challenges of the technological progress.

Fading of Existing Technology Dominance

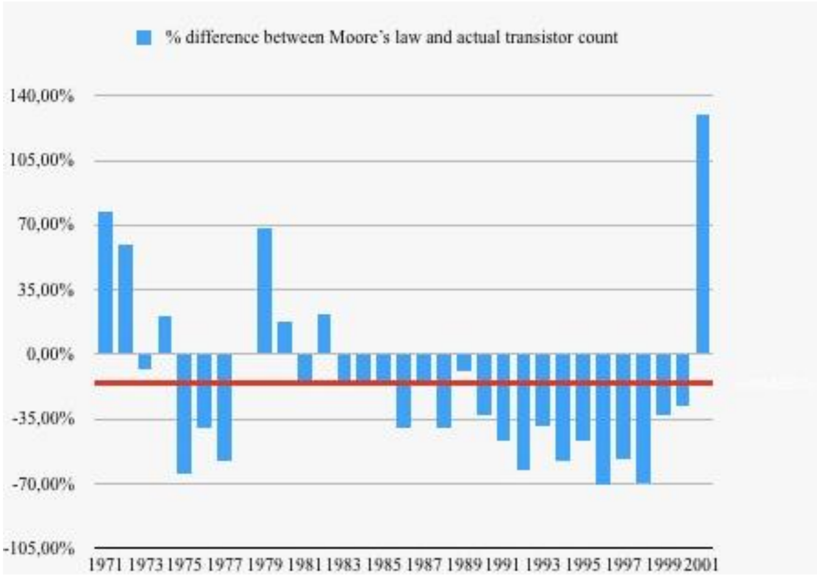
Since its early days in the 1960's, the optical-lithography technological regime had dominated the Lithography industry. An optical-lithography machine is a delicate interplay between lens, energy source, mask, and resist technology. To stay aligned with Moore's law, industry leaders were engaged in advancing technology in both evolutionary and revolutionary manners. As a result, five generations of optical-lithography technology had been introduced to the market by mid-90 (for an overview of technological generations in this industry, see Adner and Kapoor, 2016). Each generation came with architectural change, as well as a significant improvement of the energy source (Henderson & Clark, 1990). To give an impression, while the then dominant generation, the I-line 365 nm stepper, was running the market around mid-90s, the next generation, DUV-248 nm scanner, already entered into the market, and feasibility studies on the subsequent generations of DUV machine, the 193 nm ArF were in progress.

However, while optical lithography was still very active and continuously advancing, there was a growing conviction among industry actors that optical-lithography technology was approaching its physical limit (Ito & Okazaki, 2000). Indeed, the industry was lagging behind Moore's Law in the mid-1990s. Therefore, something significantly different from the current technological regime seemed necessary. By the mid-90s, some of the industry's main actors had already invested in substitute technological regimes. In general, two alternative technological regimes had started their research phase since mid-80, namely X-ray and particle-based technological regimes (Figure 3).

The Emergence of Rival Technological Options

X-ray technological regime, including hard and soft X-ray. X-ray is a form of high-energy electromagnetic radiation, with a very short wavelength. X-ray technologies use x-radiation to project the image through the mask to the wafer without using any lens in their

FIGURE 3: The situation of technology edge in industry compared to Moore's law expectation.



architecture. X-rays with higher energy level and shorter wavelengths are called hard X-ray, while those with lower energy level and longer wavelengths are called soft X-ray. However, as soft X-ray is also close to ultraviolet wavelengths, it is also called Extreme Ultraviolet (EUV).

IBM hugely invested in hard X-ray printers since the mid-70s. Japanese institutions and firms such as NTT, Nikon, and Hitachi studied and invested in soft X-ray (EUV) technology since the 80s.

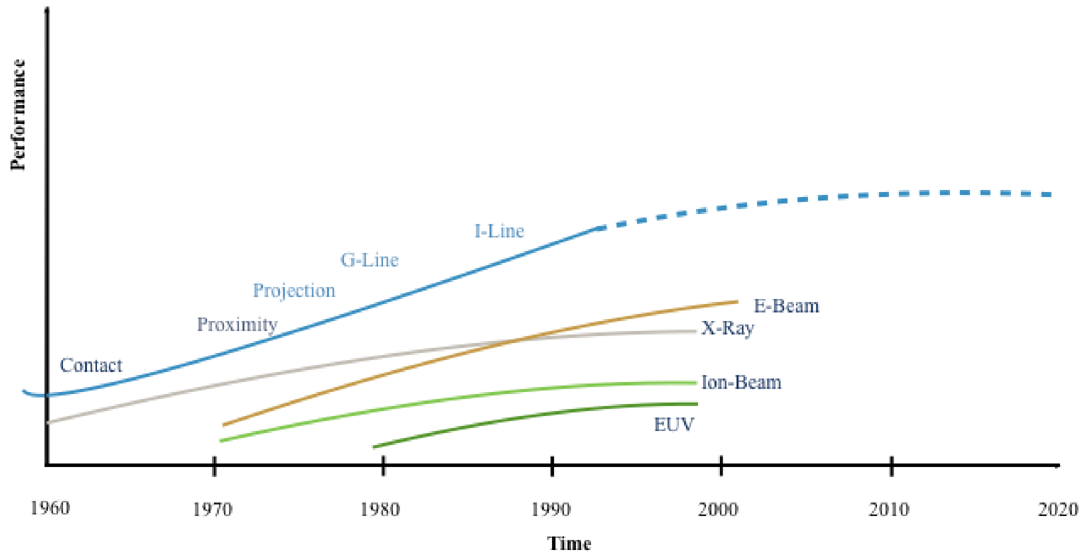
Particle based technological regime, including E-beam and Ion beam. Particle based- technologies use electron or ion beams to print directly a pre-programmed pattern without using any mask on the wafer.

E-beam lithography is the practice of scanning a focused beam of electrons to draw custom shapes on a resist that covers the wafer. E-beam was seen as a very promising technology, but electron scattering and slow printing hurt both its resolution and throughput. The second option in particle-based regime is Ion-beam or IPL technology that uses ions to make projections on wafers. Ions cause less scattering issues compared to electrons in E-beam and light in optical lithography. In addition, ions are heavier than electrons, so it is easier to get ions closer to each other than electrons to enable the required alignment for printing.

IBM's investment in E-beam writers started in 1980s, and ASML and Siemens started supporting a research project on particle-based Ion-beam printer technology in the mid-1990s. However, none of these had shown enough progress to be considered as the ultimate substitute technology by that time, so there was significant uncertainty about the most promising choice of replacement for optical-lithography technology.

The choice of the new technological regime was very critical, because on one hand, the industry's success in following Moore's law depended on the choice of the right technological regime, while on the other hand, the industry could not afford to concurrently develop two technological trajectories, because of Rock's law. Therefore, there was a collective conviction that there could be only one winning technology. Figure 4 shows our own qualitative interpretation of the different technological options in the era of ferment.

FIGURE 4: Development of technological options for lithography



INCUMBENT'S ENGAGEMENT IN THE ERA OF FERMENT

By the mid-1990s, various economic downturns and continuous demand for technological progress had caused industry shakeouts, and two of the major lithography suppliers had been able to keep a dominant market share. Nikon and Canon were market leaders with over 45% and 25% of market share, respectively, and ASML, a fast-growing spinout, had just joined the leaders with a market share of 25%.

ASML: A Growing Incumbent Firm

ASML, a spinout of Philips, had been struggling to survive in its first ten years (1984 - 1994). In addition to the natural challenges that a new venture has in its early life, the lithography technology ASML inherited, stepper optic-lithography technology, had already suffered a long and bumpy road in the NATLAB laboratories of Philips between the mid-'70's and 1984 (Linden et al., 2000). As the CTO of ASML described the condition: "[Until then, it was] *seeing the rear lights of the competition, and you try to be as fast as possible and stay out of trouble".*

Nevertheless, ASML showed significant growth after introducing the I-line machine (PAS 2500) based on its own production architecture in 1992 and overcame the major industry downturn of the early 1990s. Following its fast growth pace, ASML steadily separated from its parent, Philips, which had been still in charge of R&D and intellectual property protection. ASML set up its own R&D and an in-house IP department, and went through IPO in 1995. ASML steadily increased its R&D investment in the subsequent years (from almost €57 million in 1996 to €144.5 million in 1998). ASML hired a new research manager to lead a team of scientific researchers to set up a fundamental research program to look beyond the horizon. The assigned scientific research team had a close interaction with the development division and system-engineering department, but also had the required freedom and authority to act autonomously without engaging in day-to-day development stress.

> *"I think the question was so business critical that they (ASML) wanted to take full control themselves. Do not outsource this question. You can outsource the*

activities, but not how do I address the question and how do I make, give an answer to the question. What will happen after optical lithography?" – Senior Vice President Research ASML

By the mid-1990s, ASML found itself as an established incumbent with the required confidence and resources to choose and plan its future path. While ASML was still busy establishing its status among the market and technology leaders in the industry, the increasing difficulties and complexity in the progress of optical-lithography technology signaled the imminent end of the domination of the current technology. ASML started to consider the emerging technological options in order to remain the industry's provider of leading technology solutions.

Stage 0: Identification of Emerging Technologies as Real Options

Application of Simple Scientific Rules in the Initial Assessment of Options

Moore's and Rock's laws impose strict long-term expectations on the resolution and throughput of any technological option. ASML researchers were well aware of these fundamental laws. They relied on the basic science of physics and on economics to develop a set of simple rules to evaluate the prospect of technological option fitting these fundamental laws. These simple rules provided ASML with a clear theory about the success factors of each technology in its technology search process, and prevented it from falling into the trap of trial and error in pushing the performance of each technological option (Gavetti & Levinthal, 2000).

The ASML research team relied on these simple rules in its exploration to identify the technological options in which the firm should invest. Two technological regimes, particle based, including E-beam and Ion-beam, and X-ray, including hard and soft X-ray, were considered to be the viable options to replace optic-lithography technology. At the first step, ASML was convinced that hard X-ray could not be a promising option to invest in. By the mid-

1990's, IBM had invested heavily in hard X-ray for many years, and some of the industry leaders expected hard X-ray to be the nearest option to market introduction when the search for NGL started; however, ASML abandoned this option in the first place. The rationale behind this decision was that the extendibility of X-ray technology was questionable. First, as the hard X-ray architecture is not equipped with a lens, the resolution of the machine remained a direct function of the wavelength of the energy source, a significant limitation that the industry already experienced in its very first generations of lithography technology. Second, one of the fundamental complementary elements of X-rays machine, the mask, had considerable technological issues that could limit the improvement of the energy source (i.e., reduction of wavelength to reduce the node of production). Therefore, ASML was convinced that the technology was 'end-of-life' even before it reached the market.

Outside of the two challenging technological regimes in the era of ferment, imprint was another technological option that was considered later on, but it did not receive any real significant research dedication from ASML. Although imprint was mentioned in the 90s, it was not one of the initial NGL options and it became more in fashion in the early 2000s receiving extensive attention for over ten years. The basic idea behind imprint is to write a mask and to press it into the resist on the wafer. Although ASML engineers were challenging their technology leaders to consider this technology, it never became a serious consideration for the organization. The technology was reckoned too sensitive to defects, so it could not be a real option for mass production, and ASML was not interested in niche markets in which imprint technology might be suitable.

Stage 1: Acquisition of Technological Options via Joint Ventures

After dropping hard X-ray and Imprint as feasible options, ASML focused on the three remaining technological options. In terms of compatibility to the existing lens-based optical-lithography ecosystem, mirror based Soft X-ray, or EUV, was the closest technology. However, ASML still also became actively involved in research projects for E-beam and Ion-beam applications. They tried to keep an open mindset towards other solutions by investing in all options that might offer a solution to the challenge at hand. As the Senior Vice President of research at ASML recalls:

> *"We tried to be not biased which is always difficult. Because EUV was the best fit to our existing partners (e.g., Carl Zeiss etc), but we told ourselves we should be objective in the choice".*

By doing so, they aimed to overcome their own preference bias and to be open to other possibly viable options, because they could not afford to bet on the wrong option. In the following, we explain the rationale behind of ASML's investment in each of these technological options.

E-beam. In the Philips Natlab laboratories, there were two research groups, one for optic-based lithography, which was the stepper group that was finally spun-out to become the ASML venture. The other one was the E-beam group, which was believed to be the one with the most potential. In addition, ASML had already engaged in a research project on E-beam with a renowned research group at Delft University in the Netherlands. Therefore, technological knowledge about E-beam was more accessible to ASML than that for the other options.

ASML made a visit to Bell Labs in the late 1990's, and considered a collaboration with Applied Materials and Bell labs. In order to do so they started a joint venture named eLith. Bell Labs was to provide the scientific fundamentals and ASML and Applied Materials were on board for engineering and commercialization of the technology. The goal of eLith was to push the technology further in order to make a volume-production proof of concept and to test the technology's potential for commercialization. eLith not only was a good setting to appraise the E-beam technology's potential, but also provided ASML with the chance to access the knowledge and capabilities of a top research institute such as Bell-labs and complementary resources of a microelectronic device producer in the US such as Applied Materials.

Ion-beam. In the early 1990's, DARPA (Defense Advanced Research Projects Agency) in the US showed interest in IPL (Ion Protection Lithography) technology. However, IMS, a Vienna-based startup, had the most advanced knowledge of this technology, and DARPA as a strategic US entity could not directly fund a non-USA effort. Therefore, they formed a joint venture (JV), called Advanced Lithography Group (AGL), which terminated in 1996 due to DARPA's shift towards hard X-ray technology.

Collaborative R&D efforts were continued in Europe, were ASML joined, together with TNO, a consortium of IMS and Siemens, and later on Infineon, as a client sponsor. This project was part of a 4-year research program starting in 1997 which was financially supported by the MEDEA grant program of the European Union. ASML became interested in this technology and since the research effort was supported with EU grants, there was a low entry barrier to enter into this option. In this consortium, ASML shared its technological knowledge on alignment systems that was its main competitive advantage.

Soft X-ray or EUV. EUV research efforts were organized in two main settings. On the one hand, there was a research initiative of ASML with its close European research partners: Philips, Zeiss, IMEC, Oxford Instruments and TNO. Between 1998 and 2000, ASML worked together primarily with Zeiss and Oxford Instruments in the EU-backed EUCLIDES grant program to find solutions for the main potential show-stoppers of EUV. After the EUCLIDES program finished the EU continued backing the development of EUV in its MEDEA+ program between 2001 and 2004, followed up by the More-Moore program after that.

On the other hand, an industry-wide research initiative, called EUV LLC, was founded in 1997. The goal of the EUV LLC was to overcome the most fundamental issues in the development of the first Proof of Concept (POC) of EUV machines. Intel initiated this research consortium, and Motorola and AMD joined it, and later on also IBM, Infineon, and Micron. ASML joined the EUV LLC consortium from the beginning to get access to the technological knowledge that they lacked in EUV at the time. However, in order to join EUV LLC, they first had to negotiate with a US governmental inter-agency committee, CFIUS[12], to get permission. In the summer of 1999, ASML finally received the permission and joined the two other, US-based, lithography equipment manufacturers in this consortium: USAL (a newly founded spinoff of Ultratech) and the Sillicon Valley Group (SVG) (which was finally acquired by ASML in 2000).

Table 1 provides an overview of the different research settings in which ASML was engaged during the choice for the NGL. The level of ASML's engagement in each technological option was a function of the perceived prospects, networking opportunities, and availability of funding for that option. In EUV technology, ASML engaged in research collaboration with its long-term partners as well as in a research consortium with industry leaders. For two other options, ASML was involved in a somewhat looser form of collaboration.

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[12]CFIUS is a governmental inter-agency committee reviewing the implications of foreign investments on national security. Especially the influence of investments on crucial technology positions of the U.S. are being reviewed in this office. ASML was permitted access to the EUV LLC after reaching an agreement with the DoE (Department of Energy), in which was negotiated that ASML had to produce any EUV tools that it would sell to the U.S. in the U.S., in comparable production facilities that it had in the Netherlands.

TABLE 1: Different research settings of ASML

Technologies in consideration	**EUV**		**SCALPEL**	**Ion-beam**
Industry champion	Intel		Bell Labs	Siemens/Infineon
Organization of R&D efforts	Joined European research with close partners	Consortium EUV LLC	Joint venture ELith	Joined research
Main parties involved	Zeiss, Oxford instruments, Philips, IMEC, Zeiss, ASML	Intel, Motorola, AMD, IBM, Infineon, Micron, USAL, SVG, ASML	Bell Labs, Applied Materials, ASML	IMS, Infineon, ASML

Engaging in the development of NGL options not only provided ASML with the required technological knowledge to become leading in the possible NGL in the future, it also improved its status and legitimacy as a technology leader in both the European and the US market. This privilege helped ASML to exercise its influence in the facilitation of the selection process and to establish itself as the market leader of the future.

Stage 2: Managing the Development and the Eliminative Selection of Technology Options

Industry Mechanisms to Navigate the Selection Process

Pouring hundreds of million dollars into studying and developing various technological options just in the research phase, together with the collective consensus that the winner technology would take it all, justified a collective mechanism to facilitate and institutionalize the choice of the NGL. SEMATECH [13] took on this critical role. SEMATECH held meetings annually between ‘97 and ‘03 involving around 100 expert participants from top industry actors, ranging from chipmakers to suppliers and renowned research institutes. Participants engaged in workshops led by front-runners of the different technologies. At the end of each meeting, all parties voted on the feasibility of each technology to be introduced to market within the next decade. These voting sessions were consultative, but were influential in the decision of clients and investors, so the results put a significant institutional pressure on the technology developers to either continue or abandon their technological options. Therefore, during these meetings, participants had a sense that they were involved in the ‘decision of the century’ that would set the course for the years ahead.

Eliminative Process within ASML: Shakeout in the Technological Option Portfolio

ASML had a clear preference for EUV when the experiments started. However, they were willing to be wrong and change their course of action when other technologies were more likely to suit the needs of the industry. Therefore, all experiments ran for at least two years before ASML made any decision. The setup of the different options was to strive to build a working demonstrator tool and to track its progress by progressive reduction of the list of critical bottlenecks for each technology.

[13] SEMATECH was a joint consortium formed by the USA government and major American IC manufacturers in mid 1980s. It originally supported new technologies and develop roadmaps for the future of semiconductor industry to keep US-based semiconductor companies competitive, but it took a more global approach later in late 90.

Between 1997 and 2000, it became clear that EUV was building momentum in the industry. It was making relatively more progress and was facing fewer fundamental issues than particle-based technologies. However, EUV was still facing massive practical and engineering challenges, and there was still not any proof of concept warranting the functionality of EUV. Therefore, it was hard to make a proactive choice for EUV technology, so ASML kept the options in the particle-based regime alive and let them run until it became clear that none of them would be able to meet the demands of the fundamental laws. According to the SVP of Research at ASML: *"we delayed the decision as long as we could afford, to pull the plug (on the other technologies)"*.

E-beam. From the beginning of the E-beam project before and during the eLith joint venture, ASML was concerned about the progress of this particle-based technology; however, they needed more experiments to prove all their assumptions. As the work unfolded, both technological and collaborative issues slowed down the progress. On the technology side, the particle-based nature of technology came with fundamental challenges that restricted the throughput and productivity of the technology. Indeed, electrons repel each other so the extendibility of the technology by reducing the distance between electron beams, and improving the throughput by increasing beam current, comes with blurring problems. In addition, any metal objects in the operation plant also create blurring issues, due to the E-beam machine's sensitive magnetic field. On the collaboration side, there were significant organizational and cultural challenges that made the collaboration between Bell Labs, a proud scientific institution, and Applied Materials and ASML, two practice-oriented companies, difficult.

Therefore, the work progress fell behind very soon. ASML tried to push the technology harder and brought external experts to assess the potential and progress of the technology. Nevertheless, the issues of the technology were caused by the rules of fundamental physics, so

ASML was convinced that even if all daily technological and collaborative issues could be solved, E-beam technology would still not be going to be its long-term technological option of choice. Despite the fact that the other partners wanted to keep the JV alive and some IP issues that would have to be resolved, ASML finally withdrew and terminated the eLith JV early 2001, only 14 months after its foundation. After the eLith termination, Bell Labs continued SCALPEL developments for two more years before all efforts stopped.

Ion-beam. The IPL program was the only program to deliver a working prototype by 2001. The imaging of the IPS tool, despite having its issues, was also a lot better than what was accomplished by the other technologies. However, when the 4-year IPL research program ended in 2001, most efforts in this technology as an NGL stopped soon, for both technological and institutional reasons. IPL technology suffered from the typical problem of particle-based technologies with respect to the image, the throughput capacity, and some architectural elements that limited its extendibility. In addition, the market was moving towards EUV, for technological reasons as well as the interest of heavyweight Intel. The organizational setup of the collaboration enabled ASML to withdraw easily from the program once its term was finished, and so they did as the IPL program finished.

ASML's Influence on the Selection Process

The chip manufacturers were the champions of NGL development to keep up with Moore's law, but lithography equipment suppliers were the ones that finally had to deliver the solution. ASML took advantage of its geopolitical situation and its networking to take a strategic position in this process. First, the US government did not accept non-US based suppliers to be part of the EUV LLC consortium, but US suppliers dramatically lost their market power in the early 1990s. ASML, as the only non-Japanese leading supplier of the industry, took advantage of this situation and successfully negotiated with the US government to join EUV LLC. In addition, ASML later acquired US-based SVG Company to strengthen its growing ties with major American clients and establish its strategic status. Second, ASML was engaged in different technological options and became the natural choice for the development of proof of concepts for each option. Therefore, ASML's decisions to keep or abandon a certain technology option were highly influential on the industry's course of action.

The level of ASML's commitment to the different NGL options was already an important signal to the rest of the industry, but ASML's decisions to abandon particle-base E-beam and IPL technologies had a decisive influence. Once ASML abandoned IPL, IMS was not able to compete alone to remain in the main market of lithography. Additionally, the SCALPEL technology was also not able to push to the market after ASML left. Both technologies had difficulties to find additional funding when ASML left and after a while were dropped from the industry's roadmap, which was formulated based on industrial experts input and published by SEMATECH in 2003.

Stage 3: Exercising the Option of Choice in the Twilight of the Era of Ferment

After 2001, ASML exclusively focused on EUV development. Both initial consortia, EUV LLC and EUCLIDES, ran until 2003. The EUV LLC consortium had delivered a basic Proof of Concept (POC) machine, yet the timing of rolling out the EUV machine (or in other word, exercising this technological option) was crucial yet uncertain. At that time, the technology was still highly fragile, and although there were no fundamental barriers in theory threatening the progress of EUV, there were still massive practical challenges standing between the prototypes and a working production technology. Therefore, ASML decided to keep investing in EUV as a research program. Nevertheless, ASML also built two basic alpha prototypes and in 2006 shipped them to two global semiconductor-testing facilities, IMEC in Belgium and one facility in Albany (U.S.), to see how potential customers responded to the new technology, and to establish the status of EUV as the NGL within the industry. In the meantime and as another reason for the postponement of the introduction of EUV, new technological solutions in optical-lithography pushed the bar higher for the entrance performance of EUV.

The Hidden Options: Architectural Innovations in the Current Technological Regime

At the beginning of the era of ferment, the industry actors believed that the NGL technology regime would directly dominate the market after the last generation of optical lithography (i.e., DUV 157). As described above, it became clear soon that this would not easily happen.

Despite its engagement in multiple NGL technological option, ASML continued to heavily invest in the extension of existing optical technologies. ASML believed that it should be successful in their main business to be able to afford pushing their NGL venture. As the ASML CTO stated:

> *"You have to make sure you don't get lost in the future, because the future is not going to make you money, you have to focus on the short-term as well."*

As long as NGL technologies were not mature enough, the organization still had the obligation towards its customers to enable them to produce affordable chips in the current technological regime.

The first step on this way was the introduction of the dual-stage TWINSCAN technology in 2000. The TWINSCAN was mainly a process optimization architecture that enabled optimal use of the optical system, the most expensive element of the machine, by using two wafer stages rather than one. ASML's main competitors Nikon and Canon never introduced comparable systems to the market, and ASML became the market leader with TWINSCAN in 2004.

The second boost for the extension of optical lithography was immersion technology, an unexpected finding that was introduced around 2004. The industry initially believed that 157 nm would be the natural successor of the 193 nm in DUV family. However, the development of DUV157 faced significant issues with the mask and resist. In the meantime, the concept of immersion technology was being discussed actively by the industry around 2001. The basic idea is that immersing the lens in liquid, instead of air, increases its resolution. In fact, this is a very well-known principle used in microscope technology for years and it had already been proposed for lithography applications in the late 1980s. However, it took the industry a while to realize that H2O would be the best liquid. After that surprisingly difficult stage, ASML took advantage of the compatibility of its architecture with this solution and introduced immersion machines in 2004. Indeed, it turned out that immersion was an enabling technology for at least a few generations of products in the optical-lithography regime, which also meant the end of the DUV157 program.

However, ASML was initially not leading in the third and the last extension of optical-based lithography: double patterning. Double patterning means that rather than projecting an image in one exposure on the wafer, multiple exposures are used to enable smaller pictures at higher resolutions. This solution was a breakthrough as it provides significantly smaller nodes with the same generation of machines. The first impression of ASML when double patterning technique as another extension to existing optical technological regime was introduced, was that this new technique would cost them their EUV business. As the CTO of ASML explains:

> *"So we keep on innovating immersion ... but then the customers were running out of steam on immersion and their solution was double patterning…. When I first heard about it I was afraid because I thought this might cost us business. It took me a while and I still remember the CTO from Micron, and it must have been somewhere around 2005 he called me out of a meeting …, and he said I have to*

*tell you something and he showed me the double patterning process and said this might have an impact on you. And I was going out of his office and was saying s**, and I was thinking about it and I quickly came to the conclusion this will save us."*

Indeed, the new extension offered additional time for the development of EUV, and surprisingly actually supported the business case of EUV, as follows. Double patterning technique comes with a cost. It imposes more lithography work on the same number of wafers, so as the design becomes more complex, the required number of exposures, and the demand for higher performance in overlay, the precision of the second round of printing, paradoxically increases. Therefore, projecting the image in one exposure with EUV is more efficient than to continue the complex process of adding layers in patterning techniques with DUV machines.

Enduring all these years, ASML had continued to invest in EUV developments, and they finally shipped their first pre-production tool in 2011. The R&D investment in EUV had continuously increased, so in order to keep up the investments in 2012 ASML issued shares that allowed its largest customers, TSMC, Intel and Samsung to take a share in the company. Collectively, these customers invested billions of dollars to sustain the progress of the development. ASML shipped the first complete machine in 2013; and the first machine for volume production in 2017. In 2018, EUV has finally become mature enough to be sold as a feasible technology for volume production and has claimed its position as the de facto NGL.

DISCUSSION

In this study, we explored how ASML successfully navigated the challenging dynamics of an era of ferment during a major technological transition in lithography equipment industry. To be able to understand the rationale of ASML's actions, we also got a deep peek at underlying socio-technological dynamics of natural selection processes in the era of ferment. In consequence, our findings not only shed light on the course of an incumbent's actions in the era of ferment for both theory and practice, but also offer a novel insight into the dynamics of this era. To this end, we separately discuss these findings in the light of the technology change literature and the real option perspective to decision making under uncertainty.

From Onset to Twilight of the Era of Ferment: An Alternative Explanation

Our detailed examination of socio-technological processes offers novel insight into the rise and dynamics of selection processes in the era of ferment. The discontinuous model of technological evolution perspective posits that an emerging superior technological regime discontinues the existing dominant one and commences a tough competition between the new and old technological regimes, as well as between the design alternatives within the new technological regimes (Anderson & Tushman, 1990). However, this model remains silent about how a new technology, which naturally evolves gradually, can suddenly emerge and out-compete the prior technology. Levinthal (1998) argued that speciation, "the application of existing technology to a new domain of application", addresses this dilemma (p. 217). Accordingly, technologies evolve gradually but can discontinue the prior technologies of other domains if they can meet their demand criteria (Adner, 2002; Levinthal, 1998). Our findings shed light on an alternative explanation. Sood and Tellis (2011) classified technology disruptions into upper attack and lower attack. Upper attack happens when the performance of new technology is higher than the existing one from the beginning, contrary to lower attack. Upper attack is mainly the case for high-tech industries such as semiconductor industry in which there is a continuous demand for high-end technology. Our study illustrates the dynamics of the era of ferment in the upper attack. In this case, the era of ferment starts when the expected long-term performance of emerging technologies within the same domain challenges the future of existing ones. A competition takes place between variations of old and new technological concepts and designs, and industry-wide social-technological mechanisms determine the winner. This explanation, aligned with continuous models of technological change (Foster, 1986) and similar to Levinthal's (1998) account, considers the gradual progress of technology, but offers new insight into underlying social-technological mechanisms in the era of ferment when an upper attack is raised within the domain.

Our observations show that the selection mechanism in the era of ferment is 'eliminative'. That is, rather than the triumph of one technological option over the others in such a technological contest, alternative options are fading away one by one by losing the required support and legitimacy for further development from the experts and investors. EUV technology has never been chosen as the winner in NGL contest; indeed, the other technologies lost their chances by losing the institutional support of experts and the financial support of industry champions. For example, the CEO of IMS, the leading company in Ion-Beam technology, stated:

> *"So, the industry came to the conclusion that it doesn't make sense to continue [with Ion-Beam technology as,] this will lead us to excellent research, but it would not lead us to production. And so… finally you have to come to the production environment."*

The selection process in the era of ferment looks like the inductive elimination procedure in natural science in which alternative hypotheses are eliminated one by one after each experiment (Norton, 1995). Here, the scientific-based, but socially constructed hypothetical evaluations of experts regarding the prospects of each technology have been tested over time in an eliminative process. This observation is also in line with the evolutionary theory in which the survival of the fittest implies the extinction of failures.

On another note, our findings also provide insights into the dynamics of technological change. Consistent with Adner and Kapoor (2016), we show how technological changes can take a long time if the existing technology continues to extend, and complementary elements in the technology ecosystem limit the progress of the new technology. Interestingly, the functionality of technology in this transition can change over the course of this process. EUV was supposed to take over the optical-lithography by offering smaller nodes, i.e., as a product innovation; however, EUV entered into the market as a process innovation as it offered the same nodes, but with a reduction of production cost in semiconductor manufacturing as well as a promising extendibility capacity.

Incumbent Actions in the Era of Ferment: A Real Option Perspective

As the most important contribution of this study, our findings highlight the success factors of incumbent firms in decision making under uncertainty. First, we found a convincing match between the stages of the era of ferment and the life cycle of real option, that helped us to investigate the rationale of ASML's action in more detailed. As it is illustrated in Figures 1 and 2, era of ferment starts with the emergence of new technologies that challenge the continuity of existing technology dominance. Given the fact that technologies grow gradually, a successful course of incumbent actions starts even before this stage, when incumbents actively search for the identification of emerging technological options that may threaten the existing technology in future, as well as of hidden opportunities for the extension of existing technology to outcompete the emerging technologies or postpone their triumph. The next stage is marked with the raise of decisive competitions over performance and compatibility with the supporting ecosystem between emerging and existing technologies. The next dominant technology is the one that survives the eliminative selection procedure of this crucial stage. In this stage, successful incumbents properly manage their technological options in term of preservation of selected technology and abandonment of eliminative ones. However, what may make the decisive difference between successful incumbents and others in the management of this process is timing. As the Senior Vice President research of ASML stated:

"But you like to have of course the head start. And that's your way, because in this industry timing is everything if you are two years earlier than your competition, you have a very big advantage. Now that's the price to gain."

Our case study showed while some of technology leaders had made considerable commitments in the development of emerging technologies earlier than ASML in the first stage, they lost their edge in the second stage because they were not able to make a timely decision to abandon their failing option due to their prior commitments. For example, IBM had hugely invested in hard X-ray and E-beam technologies, but they continued with their investments even when the industry actors convinced that these technologies are not viable options. Therefore, timely creation or acquisition of technological options during the first two stages has a significant influence on the success of an incumbent in the next stages. Likewise, if ASML would have invested in each of its technological options earlier or later, their benefits from these options could have been dramatically different. There is a sweet spot in the timing of the acquisition and exercise of options. ASML's investment in each option was not too early, so they did not bear heavy research investment, but it also was not too late to let the competitors replace them. On the technological side, while the late investment in the technological options may prevent incumbents catching up the steep rate of technology development and competition in the second stage, the early investment in the first stage also may make an unnecessary escalation of commitment that prevent incumbent making timely decisions in the second stage. Finally, this turbulent period ends with the domination of the winner technology. The timely abandonment of eliminated technologies and making a commitment to exercise the selected technology in this stage can complete the successful course of action during this period. While Nikon had invested in the development of EUV technology early on, they did not keep their commitment to this expensive and ambitious technology, possibly due to the existence of other options in their diversified business portfolio. Twenty years later- now- Nikon lost the majority of its market share to ASML, thanks to EUV technology.

Our findings also highlight the importance of simple rules in making complex decisions under uncertainty in all these stages (Bingham & Eisenhardt, 2011). ASML relied on basic science and the two industry laws, Moore's and Rock's, and developed simple rules that governed its decision-making over complex technologies under uncertainty. ASML applied these simple rules in the examination of the hypothetical ultimate frontiers of each technology with respect to the resolution and the throughput. For instance, ASML convinced to drop the most advanced technology at that time, hard X-ray, as they did not see enough room for the extendibility of this technology. In hindsight, industry experts believe that if one of the EUV's rival technologies had been selected, that technology could not have been extended enough to replace the continuously progressing optical lithography. One implication for the valuation of technological options in the era of ferment is that incumbents should consider the fundamental scientific attributes of technology to assess their long-term feasibility and extendibility, rather than their current performance.

In addition, our findings offer novel insight into the boundary conditions of the real option perspective regarding the type of uncertainty in real option portfolios (Adner & Levinthal, 2004). Received research proposes that exogenous uncertainty is out of firm's control and justifies a passive form of learning in which decision makers can wait to receive more information without the need to take a costly action (Chi et al., 2019, p. 541; Kulatilaka, 1995). Therefore, a deferral option allows the decision makers to obtain new information without taking any specific actions that entail investments in time, effort, or money (Chi et al., 2019). However, endogenous uncertainty can be resolved by the firm's action over time and justifies an active form of learning, because the degree of uncertainty is a function of firm's action to obtain more information (Chi et al., 2019; Cuypers & Martin, 2010). Therefore, a sequencing option allows the decision makers to participate in active learning with a minimum required investment (Chi et al., 2019; Kogut, 1991) that to some extent violates the boundary condition of real option perspective (Adner & Levinthal, 2004). In sum, the level and type of uncertainty are crucial factors that determine the value of different types of real options. With this respect, we can elaborate on our observations regarding ASML's decisions and actions toward technological options at both individual and portfolio levels. At the technology level, as the required resources for the viable options were not interchangeable, ASML evaluated the level of their uncertainties independently to set the level of its engagement in each technology. When the prospect of all technologies seemed relatively uncertain to ASML at the onset of the era of ferment, ASML engaged in all viable technological options. Later, when the promise of EUV increased, ASML increased its commitment toward EUV technology and entered into a new partnership with their long-term partners such as Zeiss, IMEC, and Philips, in addition to their membership in the EUV LLC consortium (Table 1). Moreover, they started considering the exit option in their agreements for less prospective particle-based options, E-beam and Ion-beam technologies. This observation is aligned with a real option perspective and its applications in strategic management. Under exogenous uncertainty, ASML made the minimum possible commitment to all visible options; however, when more information revealed from the industry, they sequentially increased their investment in the most promising option to collect more information and establish their position; in addition, they considered abandoning the other options.

While these technological options are individually independent, they are competing at the portfolio level. Received research suggests that when a firm forms a portfolio of competing options, the portfolio is sub-additive, as option investments overlap with one another (Vassolo et al., 2004). However, our findings suggest that the type of uncertainty and sub- or super-additivity of a portfolio can be a function of relative size of portfolio to all available options.

First, while uncertainty about each individual option in the era of ferment can be considered exogenous, engaging in other options provides firm with timely information about the other competing options and reduces the uncertainty of the whole portfolio. Therefore, when the total number of options is limited, having multiple options, regardless to their competitiveness, might be super-additive, as it reduces the risk of improper actions and increases the total value of the portfolio. However, when the total number of options increases the cost of accessing to timely information outweighs its benefits, meeting the strict boundary condition of real option perspective regarding exogeneity of uncertainty. In other words, the sub-additivity or super-additivity of a real option portfolio can be a function of the relative size of the portfolio with respect to the size of all the existing options. For example, ASML's bet on E-beam technology was under exogenous uncertainty, as nobody could predict the next generation of technology on that time and as the ASML's investment could neither reduce this uncertainty nor increase the success chance of particle-based technologies. However, ASML's investment in the other viable options, such as EUV and Ion-beam, provided ASML with timely information about almost all technological options and turned exogenous uncertainty to endogenous one at least to a certain level.

Moreover, when the portfolio size with respect to all options increases, the firm might be able to influence the overall uncertainty of its option portfolio. Hence, although it seems that competing option subsidizes the marginal value of each other at option level, the total value of an option portfolio might disproportionately increase. For example, ASML's engagement in particle-based technologies not only initially helped ASML to hedge the risk of making the wrong technological choice, but also helped it to preempt other competitors to make use of these technological options and challenge ASML. In addition, being engaged in several options boost the ASML's status as a technology leader in the industry and provided them with the legitimacy that they needed to have a say in the selection process and to receive enough support in the development of the technology of choice.

CONCLUSION

This study shows how incumbent firms can prepare themselves to be actively engaged in the era of ferment and facilitate the domination of a new technology. Being prepared increases their chance to make the right decision at the right time, and ultimately maintain dominance in both the existing and the future technological regime. Choosing different R&D approaches with different levels of commitment for different technologies offers enough flexibility for incumbents to hedge decisions and minimize risks. Finally, the ASML story shows that deploying resources to focus on both existing and upcoming technologies can help maintain and even strengthen an incumbent’s position in the old technology, while simultaneously developing the new technological regime.

ASML was not the only dominant Lithography OEM company in the industry, nor was it the only one active in multiple options and alliances. Both Canon and Nikon were investing in different alternative technological options, Canon was involved in X-ray, imprint and EUV, while Nikon invested heavily in both Prevail (a SCALPEL-like technology) and EUV. Indeed, there were several large Japanese consortia solely focus on the development of EUV technology and complementary infrastructure and capabilities around 2003. However, in the end, neither of these companies continued to invest in the long, expensive, and strenuous path that was needed to make EUV a reality. Now in 2020, EUV is finally getting a foothold in the market. VLSI, a prominent consultancy firm in the semiconductor industry, in October 2018 called EUV a “30-year overnight success story”. It was a long and bumpy road taking much more effort, time, and investments than anybody could have anticipated, but it left ASML in the unique position of being the only player in the market that can provide clients with the technology they need in the years to come.

CHAPTER 5

GENERAL CONCLUSION

R&D alliance is a multifaceted phenomenon, in which various socio-technological mechanisms operate in the interaction of partner firms. This dissertation is composed of three studies to shed light on different dimensions of firms' resources and performance in different forms of R&D collaborations. The findings of this dissertation have theoretical and practical implications with respect to the boundaries of R&D alliances. The findings of the first study suggest that dyadic R&D alliances are the proper vehicles to learn from the different problem-solving attitudes or cognitive map of alliance partners rather than acquiring their knowledge in new domains. The findings of the second study demonstrate that the performance consequences of diversity at alliance and firm levels are not necessarily aligned in multi-partner alliances, so some partners can benefit more than others, even when the alliance partnership on the whole is deemed unsuccessful. Finally, the findings of the last study shed light on the legitimacy acquisition and timing privilege to navigate the dynamics of technology change as the critical dimensions of alliance performance. These three studies tie together to the extent that they clarify the complex dynamics that exist between individual firms and their alliance partners in order to realize individual and joint value. In general, this dissertation contributes to the strategy and technology management literature by elucidating the less-explored dimensions of the firm's resources and performance in R&D collaborations. In the following, I summarize the main findings of each individual study in this dissertation.

The second chapter - Cognitive distance dimensions and inter-firm learning: Knowledge domain and knowledge architecture distance- revisits the central argument of interorganizational (IOR) literature for inter-firm learning mechanisms in R&D alliances. This study, in contradictory to extant research findings, shows that firms mainly learn from new combinations of already known knowledge domains, rather than knowledge in new domains. This study offers a deep insight into the inter-firm learning mechanisms in R&D alliances and underlines the boundary of R&D alliances with respect to knowledge transfer and inter-firm learning. The reconceptualization of cognitive distance based on two distinct dimensions, knowledge domain and knowledge architecture, extends this concept. This extended and theoretically rich concept can cover all the different proposed concepts to address the difference between firm's knowledge, such as knowledge overlap (Mowery et al., 1996), knowledge distance (Gilsing et al., 2008), and knowledge diversity (Sampson, 2007) under one umbrella.

The third chapter - Multi-partner R&D alliance diversity and innovation performance: The dilemma of value creation and value appropriation - studies the innovative consequences of three dimensions of R&D consortia diversity with respect to the locus of resources: within-firm, between-firm, and across the global network. Findings show that diversity within each of these dimensions in multilateral entities such as a multi-partner R&D alliance has an inverted U-shape relation with the total created value, but that resource-rich firms capture most of this value.

This study advances alliance research by shedding light on the complexity of multipartner collaboration as well as the disparity between value creation and appropriation. This study contributes to the longstanding stream of strategy research on the performance consequence of diversification strategy (Rumelt, 1982; Montgomery, 1985; Markides & Williamson, 1996; Jiang et al., 2010; Richter et al., 2017; Ahuja & Novelli, 2017). In the context of multi-partner alliances, as collective and voluntary organizational associations, the diversification is a consequence of the initial decision of firms at the time of alliance formation, as well as the decision of firms to stay, leave, and invite or accept the new partners during the alliance. The findings show that diversity in different types of resources leads to distinct rent variation at both MPA and firm levels. My findings also contribute to the understanding of value creation and appropriation mechanisms of MPAs by taking into account the underlying mechanisms of both the value creation at MPA level and the value appropriation at the firm level in the same study. On one hand, the value creation is a function of firms' contributed resources to MPA as well as the dynamics of cooperation and coordination of firms in their mutual effort (Gulati et al., 2012; Gulati, 1998). On the other hand, the value appropriation depends to the value of a firm's contribution, the relevancy of its resources, its status and power, and its brokerage position (Adegbesan & Higgins, 2011; Dyer et al., 2008; Lavie, 2006; Lavie et al., 2007). These findings show the divergence of these two mechanisms at MPA and firm levels in such a way that value creation in MPAs alongside with diversification in each dimension is not compatible with the value appropriation in partner firms. In simple words, what is beneficial for alliance is not necessarily beneficial for all partner firms.

On another note, my empirical approach in the identification of the technological scope of alliances in both studies is novel. I analyzed the technical content of each alliance agreement and took that part of a firm's knowledge into account that has fallen in the knowledge category of alliance technological scope. This approach minimizes the noise of attributing knowledge domains to the alliances that have never been used or created in alliances, particularly in large companies that have a very wide knowledge breadth and use different knowledge sourcing instrument (Sampson, 2007). This approach can be widely applied to research on firms' activities within specific technological scope, particularly if it is incorporated with machine learning techniques to improve its accuracy and replicability.

The fourth chapter -Incumbent success in the era of ferment: Navigation of intergenerational transition of lithography technology within ASML- addresses how incumbent firms can leverage R&D collaborations to influence the process of technological change. This study shows how incumbent firms can actively engage in and facilitate the process of technology transition, in a way to maintain their dominance in both the existing and the future technology. The findings show that timely commitment and abandonment in different technological options via R&D collaborations enable incumbents to not only manage the underlying uncertainty of decision making in this transition, but also navigate this process.

My findings offer significant insight into the dynamics of the era of ferment and the course of an incumbent's action in this era. My detailed examination of the technological selection process in the era of ferment uncovers its underlying socio-technological mechanisms and contributes to the evolutionary perspective on technological change (Dosi, 1982; Dosi & Nelson, 2013). My observations show that the selection mechanism is 'eliminative'. That is, rather than the triumph of one technological option over the others in such a technological contest, alternative options are fading away one by one by losing the required support and legitimacy for further development from the experts and investors. This observation is also in line with the evolutionary theory in which the survival of the fittest implies the extinction of failures.

My findings also contribute to real-option theory. I matched the life cycle of real options with the stages of the era of ferment to investigate the rationale of a successful incumbent's action at each stage, a rare opportunity to elaborate on the real option reasoning in such detail. My observation on the application of simple rules in the lack of reliable valuation signal to get through the whole lifecycle of real options is informative. My findings also offer an insight into the underlying dynamics of real option portfolio management. Received research suggests that when a firm forms a portfolio of competing options, the portfolio is sub-additive, as option investments overlap with one another (Vassolo et al., 2004). This study shows that when the total number of options is limited, having competitive options might be super-additive, as it significantly reduces the risk and increases the total value of the portfolio. In other words, the sub-additivity or super-additivity of a real option portfolio can be a function of the relative size of portfolio with respect to the size of all the existing options. When the portfolio size in comparison to all possible options increases, the firm might be able to influence the total risk of its option portfolio. Hence, although it seems that at the option level competing option subsidizes the marginal value of each other, the total value of portfolio options might unproportionally increase. These findings have direct implication in alliance portfolio literature.

Finally, the timing of acquisition or investment in technological options is very crucial in the management of real option portfolios in the era of ferment. There is a sweet spot in the timing of the acquisition and exercise of options. Investments in each option should not be too early, to impose not heavy research investment, but it should not also be too late to let the competitors take the option and leverage it to challenge the other options. In addition, the timing of abandonment give the chance to influence the social side of technology selection process, when the industry actors perceive it as a strong signal to accelerate the elimination procedure. This is a good example that shows how the abandonment of an option, or termination of an alliance, can increase the total value of a portfolio of options, or alliances.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Naturally, this research has several limitations. In the first two studies, chapter 2 and 3, I used archival data and employed quantitative analysis. In the third study, chapter 4, I studied a single case and ran a qualitative analysis. First, the alliances examined in the first two studies are those pertaining to R&D alliances, and although my argumentation is general and can apply to all types of alliances, there is a cautious in the generalizability of these findings to the other types of alliances (e.g., marketing, manufacturing, and supply chain). Second, I used patents to develop my main measures; however, the accuracy of patents to represent firm’s knowledge and inter-firm learning is questionable (Roach & Cohen, 2013). Finally, the fourth chapter is a single case study in a specific context of lithography technology in late 90’s. In this context, there was a general belief that industry should collectively find a solution for the next generation of technology. This condition may not hold in technology transition in more fragmented industries, so generalization of findings should be considered with caution. These findings would need to be replicated to examine the boundary of transitions that allows the successful proactive engagement of incumbent firms.

Future research may extend these studies in both theoretical and empirical aspects. From the theoretical point of view, I distinguished between two inter-firm learning opportunities in the second chapter. This approach invites future research to revisit knowledge sourcing strategies of firms. This study suggests that R&D alliances mainly provide opportunities to learn knowledge architecture rather than knowledge domain. Future studies may examine the other forms of knowledge sourcing such as M&A with this respect: which knowledge sourcing mode provides which learning opportunity.

With respect to the third chapter, further studies are needed to understand better the complexity of configuration and dynamics of value creation and appropriation in MPAs. MPAs appear in different forms and I only focus on one form (i.e., R&D collaboration) in this research. Investigating the configuration and dynamics of the other forms of MPAs may improve the general understanding about this phenomenon. Future research might also take into account the other types of performance to improve the theoretical and empirical understanding of dynamic of value creation and appropriation in MPA. This research addresses the performance of MPAs in a specific context with elaboration on the alliance scope. However, it is necessary to develop a systematic examination of alliance performance measures at the alliance level, rather than at the common focal firm level. Finally, my approach to systematically examine the diversity in the context of multi-partner alliances can apply to other relevant phenomena such as alliance portfolios and corporate firms.

The fourth chapter calls for further research on the proactive actions of incumbent firms in the era of ferment. While the current research has extensively studied the success and failure of incumbent firms to adopt new technology, the underlying mechanisms and conditions of proactive actions of incumbent firms are relatively under explored. In addition, my contribution to real option perspective suggest that we need more empirical analysis to examine the boundary conditions of sub- vs super- additivity of real option portfolios as well as the boundaries between endogeneity and exogeneity in real options. These questions are directly applicable to the context of alliance portfolio studies.

The goal of this dissertation was to provide insight into the multidimensionality of resources and the underlying socio-technological mechanisms of R&D collaborations. Answering the underlying research questions leads to novel insights and contributions to the extant literature. Nevertheless, numerous questions for future research remains.

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